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THESIS

EXPERIMENTS IN FORECASTING ATMOSPHERIC MARINE HORIZONTAL VISIBILITY USING MODEL OUTPUT STATISTICS WITH CONDITIONAL PROBABILITIES OF DISCRETIZED PARAMETERS

by

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Experiments in Forecasting Atmospheric Marine Horizontal Visibility Using Model Output Statistics with Conditional Probabilities of Discretized Parameters

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ABSTRACT

This report describes the development and application of a program to forecast important air/ocean parameters using the method(s) of model output statistics. The focus of this operationally oriented study is to forecast atmospheric marine horizontal visibility using a discrete analysis of observed visibility and the Navy's Operational Global Atmospheric Prediction System (NOGAPS) model output parameters. Three strategies (two based on maximum-probability and one based on natural-regression) are compared to two multiple linear regression methods. The primary data set is from a North Atlantic Ocean area bounded approximately by the North American coast from Norfolk, Va. to St. Johns, Newfoundland, and then eastward to about 37.5°W. Both the dependent and independent data were derived from the same basic set. New or unfamiliar concepts, in addition to the primary methodology, include the statistical division of the North Atlantic Ocean into physically homogeneous areas, two new threshold models for the application of linear regression equations, linear regression based upon a 'decision-tree' concept, functional dependence of predictors and class errors. Results show that the methodology proposed by Preisendorfer does out perform multiple linear regression.

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I. INTRODUCTION AND BACKGROUND

Model output statistics (MOS) is a technique whereby parameters output from numerical weather prediction models (predictors) are statistically processed, with observed data, to produce forecasts of one of the following categories of parameters (as predictands):

a. operationally important parameters not output by the numerical prediction model (e.g., visibility, cloud cover, ceiling).

b. model output parameters whose predictive skill is improved (e.g., surface wind, temperature) due to correction of numerical model bias and/or scale.

Historically, the methodology has consisted of generating empirical equations by a linear, least-squares regression model. This technique is used by both the National Weather Service and the United States Air Force Air Weather Service and has demonstrated operationally usable skill in forecasting numerous weather elements at locations over land throughout the world [Best and Pryor, 1983]. Attempts by the United States Navy to forecast open-ocean fog and visibility using linear regression equations have shown skills of marginal operational usefulness but exceeding those of persistence and climatology [Aldinger, 1979; Yavorsky, 1980; Selsor, 1980; Koziara et al, 1983; Renard and Thompson, 1984].

Presumably, this level of performance is due, in part, to the lack of 'calibrated' fog and visibility observations. Shipboard weather observers lack sufficient reference points to be able to accurately estimate the range of atmospheric visibility.

In the spring of 1983, the United States Navy made the decision to begin development of a MOS program to forecast operational air/ocean parameters over the oceans of the world. Primarily, because of the importance of horizontal visibility to the mariner, this parameter was elected to be the initial candidate. However, because of less-than-perfect prior results using linear regression in the North Pacific Ocean, it was decided to investigate other methodologies to determine if a better one could be found.

This study presents statistical methodologies proposed by Preisendorfer (1983 a,b,c). Specifically, three strategies, two based on maximum-probability and one based on natural-regression, are further developed, tested and applied to sets of model output parameters from both the North Pacific and North Atlantic Ocean areas. In addition, multiple linear regression is applied to the same data. Innovative threshold techniques, developed by Lowe (1984a), are also applied, and methodologies are compared.

In the following discussion, a sufficient number of terms and symbols are defined to allow readers without strong statistical backgrounds to understand the results. However,

for a proper understanding of the Preisendorfer (1983 a,b,c) methodology, readers are encouraged to read Appendix A, which contains a detailed discussion. Similarly, details on the linear regression model and threshold procedures [Lowe, 1984a) are to be found in Appendix B.

II. OBJECTIVE AND APPROACH

The objective of this study is to determine if a statistical methodology, applied to discrete values of model output and derived parameters, can improve upon the forecasting of horizontal marine atmospheric visibility when compared to linear regression. The approach is as follows:

a. define categorical groupings of visibility which relate to operational use at sea.

b. develop and apply the Preisendorfer (1983 a,b,c) methodology using July 1979 North Pacific Ocean data.

c. apply the methodology developed in b. above to June 1983 North Atlantic Ocean data.

d. compare Preisendorfer (1983 a,b,c) results to those of the Lowe (1984a) linear regression approach for the North Pacific, and North Atlantic Ocean data sets.

III. DATA

A. VISIBILITY OBSERVATIONS AND SYNOPTIC CODE

Visibility observations at sea are reported as one of ten synoptic codes, ranging from 90 (visibility less than 50 m) to 99 (visibility equal to or greater than 10 km). However, in view of the inexactness of observing and recording marine visibility, in category form, and the further degradation of its interpretation by users in forecasting, a simplified categorization of visibility was developed as follows:

category	synoptic code	visibility range
I	90-94	< 2 km
II	95-96	≥ 2 km and < 10 km
III	97-99	≥ 10 km

This scheme is based upon the following operational criteria, which applies when observed visibility falls below the indicated value:

1. 10 km (5 n mi)--United States Navy aircraft carrier flight recovery operations change from visual to controlled approach [Department of the Navy, 1979].
2. 2 km (1 n mi)--sounding of reduced visibility signals for all vessels operating in international waters. (The term 'reduced visibility' is not defined in the

International Regulations for Preventing Collisions at Sea, 1972. However, United States Navy Captains and Merchant Marine Masters generally consider it to be 1 n mi.)

B. NORTH PACIFIC OCEAN DATA

The data from the North Pacific Ocean are described by Selsor (1980) and Koziara et al (1983). Only the July 1979 model initialization (TAU00) data are used, consisting of 19 model output parameters (MOP) from the Northern Hemisphere models operational in 1979, namely, the Mass Structure Analysis, the Primitive Equation and the Marine Wind Models; and one climatological visibility parameter from the National Oceanic and Atmospheric Administration's National Climatic Data Center (NCDC), Asheville, North Carolina. Two additional parameters were derived from this set. A description of the parameters is found in Appendix C.

C. NORTH ATLANTIC OCEAN DATA

1. Area

The North Atlantic Ocean, from 0° to 80°N, was divided into physically homogeneous areas by Lowe (1984b) using an appropriate cluster analysis technique. The primary area used in this study is identified as area 3W on Fig. 1, which illustrates the North Atlantic Ocean homoegeneous areas. This area was chosen because of the relatively frequent occurrence of poor visibility as compared to the other areas.

A summary of visibility frequencies, for each homogeneous area and three visibility categories, is contained in Table I.

2. Time Period

Data from 15 May 1983 through 15 July 1983 were combined to form the June 1983 data set, hereafter referred to as FATJUNE. FATJUNE was chosen as the initial data set because of the high frequency of occurrence of poor visibility during this period. In order to maximize the credibility of visibility observations, 1200 GMT synoptic ship report data were used exclusively since this time corresponds to daylight over the entire area of study during FATJUNE.

Model output parameter data (predictors) at 1200 GMT model output time, hereafter referred to as TAU00, were used in the development of the Preisendorfer (1983 a,b,c) methodology, time not being available to pursue the scheme beyond that stage. Thus, TAU00 represents model initialization time. However, the term 'forecast' will be used throughout this study to represent the estimate of visibility at this initialization time.

3. Synoptic Weather Reports

All synoptic visibility observations (predictand data) for this study were quality-control checked and provided by the Naval Oceanography Command Detachment (NOCD) co-located with the NCDC. Those furnished observations which contain systematic observer error or are suspect or obviously erroneous, as determined from the data quality indicators, are not incorporated in the final data set.

4. Predictor Parameters

Fifty TAU00 model output parameters (MOP's) (predictor data) were provided for the period of study by the Fleet Numerical Oceanography Center (FNOC), Monterey, California. These parameters are from their current operational prediction model, the Navy Operational Global Atmospheric Prediction System (NOGAPS). All MOP's were interpolated from model grid coordinates to synoptic ship observation positions using a linear interpolation scheme. Of the 50 parameters provided, only 35 were used in the development of the Preisendorfer (1983 a,b,c) and Lowe (1984a) methodologies, the remainder being considered as either having little likelihood of importance in the forecasting of visibility or not usable due to the lack of significant digits (which were lost during the transfer from FNOC tapes to the main computer center's mass storage data system). Twelve additional parameters were derived from the interpolated MOP's. Seven of these are equations derived from a linear regression model which will be described in Chapter V and Appendix B. Each equation represents an estimate of the visibility category, which is used as a predictor. A list of all of the predictor parameters is provided in Appendix D.

D. DEPENDENT/INDEPENDENT DATA SETS

Due to the limited amount of data available to this study for each of the North Atlantic Ocean homogeneous areas, it was necessary to withhold one-third of the

observations from the developmental model to use as an independent data set. This was accomplished by the use of a counter and transfer statement in the computer programs which prevented every third observation from entering the developmental computations. To ensure that the dependent and independent data were representative of the same population, a 95% confidence interval for proportions [Miller and Freund, 1977] was established from the entire data set, for each visibility category, and the dependent and independent data sets were constrained to have visibility frequencies within these established confidence intervals. This same procedure was applied to the North Pacific Ocean data for consistency of method. Table II summarizes the dependent and independent data for both the North Atlantic Ocean and North Pacific Ocean data sets.

IV. PRELIMINARY EXPERIMENTS

A. TERMS AND SYMBOLS

The terms and statistical symbols defined below will be used throughout the remainder of this report. The formal mathematical definitions can be found in Appendices A and E.

1. Maximum-probability strategy--choosing forecast visibility categories based upon the highest conditional probabilities of visibility within a predictor interval.
2. MAXPROB1--designation of the maximum-probability strategy in which ties of the highest conditional probabilities in a predictor interval are resolved by the generation of a random number.
3. MAXPROB2--designation of the maximum-probability strategy in which ties of the highest conditional probabilities in a predictor interval are resolved by assigning the lowest visibility category, of those tied, as the forecast category.
4. Natural-regression strategy--choosing forecast visibility categories based upon the statistical average of the conditional probabilities of visibility within a predictor interval.
5. a_0--the probability of a zero-class visibility category forecast error (e.g., if visibility category I is forecast, it is also observed).

6. a_1--the probability of a one-class visibility category forecast error (e.g., if visibility category I is forecast and category II is observed).

7. a_2--the probability of a two-class visibility category forecast error (e.g., if visibility category I is forecast and category III is observed).

8. CE--class error parameter defined as $a_1 + 2a_2$, used to identify the first predictor.

9. PP--the potential predictability of visibility by any given predictor.

10. FD--the functional dependence of one predictor on another. This is a measure of functional dependence of a statistical kind and not of the deterministic kind. The term 'functional dependence' is used by Preisendorfer (1983c) and, being sufficiently descriptive of the concept, it will be used herein.

11. RSS FD--root sum squared FD. The functional dependence of a predictor on all predictors already included in the developmental model. It is equal to the square-root of the sum of the squares of the individual FD's.

12. TS1--threat score for visibility category I computed from a contingency table.

13. ATS1--adjusted threat score for visibility category I which removes the influence of the data set category frequency.

14. AA0--adjusted a_0. A contingency table statistic which removes the influence of the most frequent visibility category in a set of data (similar to a normalized value).

15. EPI--equally populous predictor interval used to discretize the predictors.

B. COMPUTER PROGRAMS

Four computer programs were developed to test the proposed Preisendorfer (1983 a,b,c) methodology. The programs are on file in the Department of Meteorology, Naval Postgraduate School, Monterey, California, 93943.

1. A program to compute a_0, a_1, CE and PP for all predictors, all strategies (MAXPROB1, MAXPROB2 and Natural-Regression) and a single number of EPI's. Statistics for the three strategies are based upon the same predictor(s) rather than the best predictor(s) for each strategy. It was determined during program development, and will be shown in Chapter VI, that, in general, each of the strategies chose the same predictor(s).
2. A program to compute FD for all predictors, on a given predictor, for a given number of EPI's, and to compute the upper 5% critical value (FD(96)) by Monte-Carlo means (Appendix A).
3. A program to construct contingency tables and to compute skill and threat scores, for both the dependent and independent data.

4. A program to generate 100 random data sets, from the marginal probabilities of the predictor(s) in the developmental model, and to compute upper and lower 5% critical values for a_0 and a_1 to be used for testing the significance of the results from the Preisendorfer (1983 a,b) methodology against chance.

C. BEHAVIOR OF a_0 AND THREAT SCORES

Before attempting a formal application of the Preisendorfer (1983 a,b,c) methodology, it was considered prudent to investigate the behavior of certain statistics as the number of equally populous predictor intervals was changed and as new predictors were added. It was found, during program testing and before a formal procedure had been established, that the independent data threat score of visibility category I (TS1) generally showed higher values than other threat scores (TS2, TS12) for the independent data. Therefore, it was decided that the dependent and independent data a_0 and TS1 scores would be compared. The statistic a_0 was chosen because it is the singularly most important scoring parameter in the Preisendorfer methodology.

The experiment consisted of choosing the first predictor as that one which gave the highest a_0 value when divided into ten equally populous intervals. Once this predictor was chosen, dependent and independent data a_0 and TS1 scores were computed for each number of intervals as the number was varied from two to 100. Prior to proceeding to the next

step, the number of intervals which gave the highest independent data TS1 score was identified and the first predictor was held at this number of intervals for the remainder of the experiment.

Subsequent predictors were chosen by both a maximum a_0 test and a functional dependence test. As each subsequent predictor was identified, its number of equally populous intervals was varied from two to 50 (or less, as the maximum array size was set at 120,000). The number of equally populous intervals giving the highest independent data TS1 was identified and held fixed for the following stage. This procedure was repeated until either six predictors were used or until a new predictor addition did not allow the comparison of at least intervals two through ten, due to computer storage limitations. It should be noted here that all of the North Atlantic Ocean parameters, not including linear-regression equations, were used in these experiments and, subsequently, some parameters were removed from consideration (Appendix D).

1. <u>Maximum a_0 Method</u>

The first NOGAPS predictor selected was SMF which was varied from two to 100 EPI's (Fig. 2a) and the highest TS1 score was obtained with six intervals. The second predictor chosen, when SMF was held at six intervals and all others at ten, was DTDP which produced the highest a_0 value for two predictors. Holding SMF at six intervals, DTDP was varied from two to 50 intervals (Fig. 2b) and the highest

TS1 score was obtained at 20 intervals. Anticipating problems with the subsequent array size with respect to the number of predictors which could be included, the secondary TS1 maximum at 16 intervals was used for further stepping. The third and subsequent predictors and their optimum interval sizes were PS at 12 (Fig. 2c), UBLW at ten (Fig. 2d) and V400 (Fig. 2e). The optimum number of intervals for V400 was not germane as no further stepping was done after this step. As illustrated in Fig. 2, the dependent data statistics aymptotically approach unity, as predictors are added, while the independent data statistics (approximate maximum values: a_0 = .70, TS1 = .35) show no further increase after the third predictor is includd, which may imply a limit as to how well the methodology performs on this particular data set.

2. Functional Dependence Method

As functional dependence is not considered until after the selection of the first NOGAPS predictor, Fig. 2a is also applicable to this method. Subsequent predictors were chosen as those having the lowest RSS FD using ten equally populous intervals. The predictors selected and their optimum interval sizes, for the TS1 score, were RH at three (Fig. 3a), DUDP at four (Fig. 3b), VOR925 at two (Fig. 3c), ENTRN at 14 (Fig. 3d) and UBLW (Fig. 3e) which was the last predictor considered. As seen for the maximum a_0 method, the dependent data statistics asymptotically approach unity. However the independent data statistics continue to grow at least through

the addition of the sixth predictor (approximate maximum values: a_0 = .71, TS1 = .38). This method gave better results than the maximum a_0 method, though it, too, may imply a limit. The results of this experiment also tend to show a preferential selection of a small number of EPI's, for best independent data TS1 score, as well as indicating that functional dependence is a relatively good choice as a deciding factor for choosing predictors.

D. BEHAVIOR OF FUNCTIONAL DEPENDENCE

Another statistic investigated prior to the formal application of the Preisendorfer (1983 a,b,c) methodology was the distribution of functional dependence (FD) calculated from 100 randomly generated data sets. The FD calculation is based upon the relationship of the distribution of one predictor to another. Because the predictors are divided into the same number of EPI's for the calculation, the probability of a randomly generated number falling into any given interval for either predictor will be the same. Therefore, the randomly generated FD values should be a function only of the number of intervals and the number of data cases (subsequent randomly generated calculations, during the formal application of the methodology, showed this to be true).

The randomly generated FD experiment consisted of computing the mean, upper and lower 5% critical values, and the standard deviation of the 100 randomly generated values for both 1526 observations (as in the North Atlantic Ocean Area

3W dependent data) and 3682 observations (as in the North Pacific Ocean dependent data) and a comparison of the results. As illustrated in Fig. 4 the FD values are similar for a given interval size differing only in the size of the confidence interval and the standard deviation. The FD values calculated for 3682 observations lie totally within the upper and lower 5% critical values for 1526 observations. Because of this relationship, future FD(96) values, used to qualitatively determine how well a new predictor will contribute to the developmental model, can be obtained by reading from the graph rather than using valuable computer resources, providing the number of equally populous intervals is less than or equal to ten.

V. PROCEDURES

A. PREISENDORFER METHODOLOGY

1. Determination of the First Predictor in Relation to the Number of Predictor Intervals

A matter not considered in Preisendorfer (1983 a,b,c) is how to chose an optimum number of equally populous predictor intervals (EPI's) into which predictor data should be divided. During the course of development, two important realizations became evident, namely, (a) there is a tendency for the methodology to give better results using a small number of intervals, and (b) the NPS W.R. Church Computer Center limits internal computer storage space to two megabytes for routine programs. The first suggested, while the second forced, the research to be limited to EPI's of less than or equal to ten if more than three or four predictors were to be considered. Once this was established, a procedure was developed to look at all EPI's within the stated limit.

The procedure involves computing the initial statistics (a_0, a_1, CE and PP) for each predictor, for each strategy (maximum-probability and natural-regression) and for EPI's of two through ten. Then, the best first predictor for each number of EPI's is determined, for each strategy, by meeting one or both of the following conditions, when considered in the indicated order:

a. lowest CE

b. highest PP

Once the best predictor for each number of EPI's is known, it is then necessary to determine the optimum number of EPI's. This is accomplished by computing threat and skill scores (Appendix E) for both the dependent and independent data and choosing, as the optimum number of EPI's, that which gives both a relatively high adjusted a_0 (AA0) for the dependent data and a relatively high adjusted threat score for visibility category I (ATS1) for the independent data. This becomes a somewhat subjective endeavor and remains as the only imprecise step in the methodology.

The statistic ATS1 is used on the independent data, instead of a_0, because it is the poor visibility categories (I and II) that are of primary forecast interest and their forecastability is manifested in their threat scores. It will be shown that, in general, the adjusted threat score for visibility category II (ATS2) and for combined visibility categories I and II (ATS12) are small compared to ATS1, or negative, and that ATS12 is maximized when ATS1 is maximized. Additionally, it will be shown that maximum a_0 does not necessarily coincide with maximum ATS1 in the independent data. Hence, if a_0 was used, the optimum combination of predictors necessary to forecast the poor visibility categories would not be included.

Once the number of EPI's is established, it is fixed for all subsequent predictors considered for the developmental

model. Holding the number of intervals fixed is not an absolute necessity, however it allows for a much more rapid development of the model. Once this number is determined for the first predictor, it is used to calculate FD for the next predictor because FD is calculated using the established number of EPI's. The next stage statistics (a_0, a_1, CE and PP) are also computed with each predictor divided into this same number of EPI's.

2. Choosing the Second Predictor

The second predictor to be included in the model is determined from its FD on the first predictor and from the increase in a_0 resulting from its inclusion. This is accomplished by computing a_0 with two predictors, namely, the first predictor, as determined above, with each of the remaining predictors. Those predictors which do not increase a_0 above its value as determined with the first predictor alone, are removed from further consideration for inclusion into the set of predictors in the developmental model. FD for each of the remaining predictors vs. the first predictor is computed. The remaining predictor with the lowest FD, on the first predictor, is chosen as the second predictor in the model.

3. Choosing Subsequent Predictors

Subsequent predictor determination is similar to the second predictor determination. Compute a_0 with N predictors (N = 1,...,M+1; M = the number of predictors already in the

developmental model), that is, the first through Mth predictors, as previously determined, and each of the remaining predictors. Those predictors which do not increase a_0 above its value as determined with M predictors are removed from further consideration. RSS FD is computed for each of the remaining predictors and the one with the lowest RSS FD is chosen as the Nth predictor in the model.

4. <u>Significance Tests</u>

After each stage (i.e., after each new predictor to be included in the developmental model is determined) it is necessary to determine if the results are significant. This is accomplished by Monte-Carlo means using the data set marginal probabilities of the predictors and assuming equal probability of occurrence for visibility categories (Appendix A). The statistics a_0 and a_1 are computed for each of 100 randomly generated data sets of a size equal to the number of observations in the dependent data set being tested, and sorted from lowest to highest. The 96th value of a_0 ($a_0(96)$) and the fifth value of a_1 ($a_1(05)$) are retained as the upper and lower 5% critical values. For developmental model results to be significantly better than chance, a_0 must be greater than or equal to $a_0(96)$ and a_1 must be less than or equal to $a_1(05)$.

5. <u>Terminating the Selection of Predictors</u>

Model development continues until any one of four conditions are met:

a. no more predictors remain to be considered.

b. results are no longer significant.

c. required computer region size exceeds that which is allowed (two megabytes at the NPS W.R. Church Computer Center).

d. independent data ATS1 does not increase for two consecutive predictor additions. (It will be shown that there is a point in the development of the model where the skill and threat scores for the dependent data diverge sharply from those for the independent data. This condition for terminating model development is a subjective attempt at taking this point into consideration.)

Once the model development is complete, contingency tables of forecast visibility categories vs. observed visibility categories, for both the dependent and independent data, are constructed. From the contingency tables, threat and skill scores for both data sets are computed and compared.

B. COMPARISON METHODOLOGY

The results obtained from the Preisendorfer (1983 a,b,c) methodology were compared to two variations of a linear, least-squares regression model. The model chosen for the comparison is that available in the BMDP Statistical Software (namely BMDP2R) [University of California, 1981] using two new threshold schemes developed by Lowe (1984c) (Appendix B). The equations developed by BMDP2R include all predictors which

increased R-squared (the proportion of the predictand variance explained by the estimation of the predictand from the multiple regression equation) by at least 1%. An excellent description of this procedure is given by Best and Pryor (1983), with R-squared being equivalent to their R-value.

1. Method 1

The first linear regression method consists of generating a single equation, trained on the dependent data, with the predictand set equal to 1, 2 or 3, corresponding to visibility categories I, II and III, respectively. This equation is used to determine threshold values (Appendix B) and is then applied to the independent data.

2. Method 2

The second linear regression method is based on a decision-tree scheme using two linear-regression equations trained on the dependent data. The first equation is generated with the predictand values set equal to zero or one, corresponding to combined visibility categories I and II (0) and visibility category III (1). The second equation is generated with the predictand set equal to zero or one, corresponding to visibility category I (0) and visibility category II (1). Visibility category III observations are ignored during this linear regression. Threshold values are then computed for each equation.

When both equations and their associated threshold values are known, the independent data set is sorted into

visibility category III and visibility category 'other' by the first equation, and the 'other' category is sorted into visibility categories I and II by the second equation. Following the development of linear regression method 1 and method 2, contingency tables are constructed, skill and threat scores computed, and comparisons made with the results from the Preisendorfer (1983 a,b,c) methodology.

VI. RESULTS

A. NORTH PACIFIC OCEAN

1. First-Predictor Selection and Interval Determination

The first predictor selected, for equally populous intervals (EPI's) of four through ten was EHF (Table III). The constant value for a_1, maximum-probability strategy, indicates that there is no predictability for visibility category II (the least frequent category in the data set) using a single predictor. A comparison of the dependent data adjusted a_0 (AA0) and independent data adjusted threat score for visibility category I (ATS1) subjectively determined the selection of five EPI's for the developmental model (Table IV; Fig. 5).

2. Selecting Subsequent Predictors

Once the number of intervals and first predictor were known, a new a_0 computation was made with the first predictor and each of the remaining predictors. Only six of the remaining 21 predictors, CLIMO, SEHF, THF, DDWW, H510 and RH, in combination with EHF, gave new a_0 values greater than that for EHF alone (.697); these comprised the pool of predictors to be considered for further development of the model. Functional dependence (FD) with EHF was computed for each of these six predictors and DDWW was chosen as the second predictor because it had the lowest FD.

For the determination of the third through sixth predictors, a new a_0 was computed as a function of all of the previously selected predictors and each of the remaining predictors. At each stage, the new a_0 computation for each remaining predictor was greater than that for the prior stage, so no further predictors were eliminated from consideration. FD was then computed, for each of the predictors being considered with each of the predictors previously selected, and RSS FD determined. At any given stage (three through six) the new predictor added to the developmental model was that one with the lowest RSS FD. The third through sixth predictors, in order of selection, are H510, RH, THF and CLIMO (Table V).

3. Determining the Final Model

The final model for the Preisendorfer (1983 a,b,c) methodology was determined by comparing the independent data contingency table statistics, from each developmental stage, and choosing the fourth stage because it gave the highest adjusted threat score for visibility category I (ATS1) (Fig. 6). The contingency tables for stage four and the related statistics for the three strategies are shown in Table VI.

4. Linear Regression

A single linear-regression equation was developed from the North Pacific Ocean data using method 1. Both the quadratic and equal-variance threshold models (Appendix B)

were applied but only the threshold values from the equal-variance model were used to compare methodologies. Table VII contains the linear regression equation, the visibility category linear regression statistics and the threshold values. Contingency tables and related statistics for the dependent and independent data are shown in Table VIII.

5. Discussion

The best results obtained from the North Pacific Ocean data were from the Preisendorfer (1983 a,b,c) methodology, MAXPROB2 strategy, as it has the highest independent data adjusted threat scores for visibility categories I and combined I/II (ATS1 = .20, ATS12 = -.05). Each of the maximum-probability strategies (MAXPROB1: ATS1 = .17, ATS12 = -.10) did better than linear regression (ATS1 = .16, ATS12 = -.13), while natural-regression shows the poorest skill (ATS1 = -.02, ATS12 = -.19).

It appears, from Fig. 6, that most of the usable forecastability resides in the first predictor chosen. This would indicate that it may be profitable to search for better predictors by combining model output parameters, conducting dimensional analysis or using linear-regression equation estimates as predictors as was done in the North Atlantic Ocean experiments which follow.

B. NORTH ATLANTIC OCEAN AREA 3W

Based upon the results obtained in the North Pacific Ocean, it was decided to use the linear regression model to

generate equations which could be used as predictors. Seven such equations were developed, each representing a different menu of parameters available to the regression model. The seven equations are included in Appendix D. The Preisendorfer (1983 a,b,c) methodology then proceeded both with and without these linear-regression equations available as predictors.

1. First Predictor Selection and Interval Determination

a. Without Linear-Regression Equations as Predictors

The first predictor, for EPI's of four through ten, varied with the number of intervals (Table IX). A comparison of the dependent data AA0 and the independent data ATS1 determined the selection of eight EPI's for the model (Table X) and, therefore, SMF as the first predictor. However, through investigator error, the model was initially developed with five EPI's and E925 as the first predictor. Therefore, both results will be presented.

b. With Linear-Regression Equations as Predictors

The first predictor for each EPI of four through ten is BM1, the predictand estimate computed by the linear regression equation developed when all of the predictors were available to the regression model (Table XI). Two of the EPI's, namely four and eight, have identical, and best, dependent data AA0 and independent data ATS1 scores (Table XII, Fig. 7), so it was decided to proceed with the developmental model for both intervals.

2. Selecting Subsequent Predictors

Subsequent predictors were chosen in the same way as described in the procedures and for the North Pacific Ocean experiment. The predictors, not including linear regression equations as predictors, are SMF, D850, RH, UBLW and ENTRN for eight EPI's (Table XIII) and E925, U700, DVDP, STRTFQ, ENTRN and PS for five EPI's (Table XIV). The predictors, including linear regression equations as predictors, are BM1, U850, D500, V850, D1000 and U1000 for four intervals (Table XV) and BM1, U500, ENTRN, DVDP and BM4 for eight intervals (Table XVI). Significance tests were made after each predictor selection and $a_0(96)$ and $a_1(05)$ values are included in Tables XIII, XV and XVI. A comparison of the behavior of critical level statistics, as predictors are added, for both four and eight intervals, is shown in Figs. 8 and 9, where array size is equal to the number of EPI's taken to a power equal to the number of predictors included at that stage.

3. Determining the Final Model

The final model for the Preisendorfer (1983 a,b,c) methodology was determined by comparing the independent data contingency table statistics, from each developmental stage, and choosing that stage which gave the highest adjusted threat score for visibility category I (ATS1).

a. Without Linear Regression Equations as Predictors (Eight Intervals)

It was determined, from Fig. 10, that the fifth stage gave the best results (MAXPROB1, independent data:

ATS1 = .19, ATS2 = .03, ATS12 = -.05). The contingency tables for stage five and related statistics for the three strategies are shown in Table XVII.

b. Without Linear Regression Equations as Predictors (Five Intervals)

It was determined, from Fig. 11, that the fifth stage gave the best results (MAXPROB2, independent data: ATS1 = .25, ATS2 = .02, ATS12 = .01). The contingency tables for stage five and related statistics for the three strategies are shown in Table XVIII.

c. With Linear Regression Equations as Predictors (Four Intervals)

It was determined, from Fig. 12, that the fourth stage gave the best results (MAXPROB2, independent data: ATS1 = .40, ATS2 = -.05, ATS12 = .12). The contingency tables for stage four and related statistics for the three strategies are shown in Table XIX.

d. With Linear Regression Equations as Predictors (Eight Intervals)

It was determined, from Fig. 13, that the second stage gave the best results (MAXPROB2, independent data: ATS1 = .32, ATS2 = -.14, ATS12 = .02). The contingency tables for stage two and related statistics for the three strategies are shown in Table XX.

4. Linear Regression

Both linear regression methods (single equation and decision tree) and both threshold models (quadratic and equal variance) [Lowe, 1984a] were used to compare with the

Preisendorfer (1983 a,b,c) methodology in the North Atlantic Ocean Area 3W. Additionally, the predictors available for regression were varied as indicated in the following description. The first regression was conducted with all available MOP's while the second regression was conducted using only the best predictors from the Preisendorfer methodology (defined as those predictors which, alone, produced an a_0 value greater than the frequency of visibility category III in the dependent data). Table XXI contains the linear-regression equations, associated visibility category statistics and threshold values. Tables XXII through XXVII contain the contingency tables and related statistics for the dependent and independent data for each of the linear regression variations.

5. Discussion

Table XXVIII summarizes each of the methodologies and strategies applied to the North Atlantic Ocean Area 3W data. In general, the maximum-probability strategy did better than the other methods or strategies. Specifically, the best results overall were obtained by the MAXPROB2 strategy, using predictors computed from linear regression equations and four equally populous intervals. The methodology without linear regression equations as predictors, and all of the linear regression results, are about equivalent. The best linear regression method is the decision tree, when all MOP's are made available to the regression model. The results

obtained without linear regression equations as predictors appear to discount the procedure established for choosing the number of equally populous predictor intervals, but lends support to the claim in Chapter V that there is a tendency for the Preisendorfer (1983 a,b,c) methodology to give better results using a small number of intervals.

VII. CONCLUSIONS AND RECOMMENDATIONS

The primary objective of this study was to determine if the Preisendorfer (1983 a,b,c) methodology applied to the FNOC NOGAPS model output parameters could improve upon the forecasting of atmospheric marine horizontal visibility, in three categories, when compared to the more traditional method of least squares, multiple linear regression. It was shown that, indeed, the proposed methodology, namely, the maximum probability strategy, was superior when predictand estimates, computed from linear regression equations themselves, were used as predictors.

The method of determining the number of equally populous predictor intervals requires further investigation. The results from the North Atlantic Ocean area 3W, without linear regression equations as predictors, showed that the proposed method was not the best, in that the number of intervals determined by the method was eight but better results were obtained with five. Additionally, only intervals of ten or less were considered here, due to storage limitations imposed by the computer center. As a result, the optimum number of predictor intervals is inconclusive.

Predictor determination appears to be adequate. At each stage of development a unique predictor was selected. The only foreseeable problem is if, during the first (initial) stage of development, multiple predictors have identical CE

and PP values, or, during subsequent stages, multiple predictors have identical a_0 and FD values. Should this occur, the model development would have to proceed, from that particular stage, with each of the identified predictors.

The methodology appears to be sensitive, in two ways, to the first predictor selected. First, there is an initial large value for the independent data ATS1 and small incremental increases thereafter for each new predictor added. Secondly, there is a large magnitude difference in the initial independent data ATS1 values between the Preisendorfer methodology without linear regression equations as predictors (ATS1 = .13; .14) and that with linear regression equations as predictors (ATS1 = .30), for the maximum probability strategy.

The best strategy is MAXPROB2, followed by MAXPROB1, and then natural-regression. Generally, natural-regression does worse than linear regression. None of the methods did well in predicting visibility category II, which may indicate that visibility would be best handled as a two-category phenomenon.

The number of independent data observations (1526) in North Atlantic Ocean Area 3W were sufficient to test the methodology. This was demonstrated by the similar results between Area 3W, without linear regression equations as predictors, and the North Pacific Ocean results (3682 observations). The small differences in the contingency

table statistics for the independent data for the two experiments can be attributed to parameters being from different models and for different months.

The following recommendations are offered for future research and to future researchers:

1. Investigate the problem of determining the optimum number of equally populous predictor intervals. Possibly, a statistic similar to the threat scores or adjusted threat scores could be used, or, simply choose the interval, between two and ten, which gives the highest adjusted threat scores for the independent data. Alternatively, adopt, without further experimentation, the number of EPI's as five, which appears to be a compromise between a gross resolution of the predictor parameter range and a fine (but too expensive) resolution of the predictor parameter range.
2. Investigate the use of potential predictability (PP) in determining the selection of predictors. During the initial stage of development, PP is computed for all available predictors and provides a measure of each predictor's individual ability to forecast visibility, but, it is not used explicitly. Perhaps computing the mean and standard deviation of PP, during the initial stage, and removing from consideration those predictors which are not greater than a value equal to the mean minus one standard deviation,

or, simply, not greater than the mean. This would ensure that only those predictors which have a relatively high prospect of forecasting visibility will be available for subsequent selection.

3. Search for better predictors which are particularly suited to visibility prediction. Recommended sources are: new, direct and derived, model output parameters (including original model output); non-dimensional parameters derived from dimensional analysis; and boundary-layer parameters such as the optical structure function (C_N^2) and extinction coefficients.
4. Investigate a two-category visibility scheme.
5. Install automatic visibility recorders on ocean-going military and civilian passenger/cargo ships. This will place visibility observations on a more objective basis and lead to improved methods of forecasting visibility, as well as verifying such forecasts.
6. Investigate new prediction models, preferably those which attempt to manipulate the observed data to correct for probable observer bias (following Selsor, 1980; Renard and Thompson, 1984). This would be unnecessary if recommendation 5 was acted upon.
7. Investigate other ocean areas and seasons to determine if the physically homogeneous area scheme is consistent and viable. Develop prediction tables and other aids specifically tailored to region and season.

8. Use a statistic other than ATS1 for choosing the first predictor and for comparing methods and strategies. It was used in this study largely because of its greater magnitude, as compared to ATS2 and ATS12. This was due to the relatively high frequency of visibility category I in both data sets. In general, this will not be the case. Because three visibility categories are being considered, and good forecasts of the two poorest visibility categories is desirable, a statistic such as ATS12 would be better suited as a consistent comparison statistic for future researchers.
9. As soon as it is feasible, eliminate from further testing the MAXPROB1 strategy in order to allow for more efficient and faster program execution. The natural-regression strategy, though it gave the poorest results in this study, should be re-examined when predictands with relatively many discrete states (e.g., ceiling) are considered. It has, in such settings, potential to out perform the more rigid linear regression technique.

APPENDIX A

A DISCUSSION OF THE STATISTICAL PROCEDURES PROPOSED BY PREISENDORFER (1983 a,b,c) FOR THE FORECASTING OF ATMOSPHERIC MARINE HORIZONTAL VISIBILITY USING MODEL OUTPUT STATISTICS

I. INTRODUCTION

The following discussion is based upon three unpublished research papers by Preisendorfer (1983 a,b,c). His proposed methodology deals with a simple statistical manipulation of model output parameters (predictors) which have been transformed from continuous to discrete quantities by grouping each predictor into equally populous intervals. The procedural approach in applying his methodology to model output statistics (MOS) forecasting, is as follows:

1. Generate predictand/predictor pairs of data using the United States Navy Fleet Numerical Oceanography Center Navy Operational Global Atmospheric Prediction System (NOGAPS) model output (predictors) and synoptic ship visibility observations (predictand) provided by the Naval Oceanography Command Detachment, Asheville, NC, and generate bivariate plots.
2. Generate conditional probability tables based on the distribution of the predictand/predictor pairs.
3. Define prediction strategies based on the conditional probabilities.

4. Compute the potential predictability of visibility from the conditional probability tables.
5. Compute skill scores of the prediction strategies and choose the first predictor.
6. Repeat steps 1, 2, 4, and 5, for multiple predictors.
7. Compute functional dependence of selected vs. potential subsequent predictors.
8. Choose the next predictor.
9. Repeat steps 1, 2, 4, 5, 7, and 8, until model development is terminated.

For demonstration purposes, an artificial data set of 99 cases, consisting of four predictors plus visibility (predictand), will be used throughout this discussion. Each predictor parameter is divided into three equally populous intervals and visibility is divided into three categories, as illustrated in Table A1. The four predictors are Evaporative Heat Flux (EHF), Fog Probability Parameter (FTER), Relative Humidity (RH) and Air-Sea Temperature Difference (ASTD). Visibility categories are defined by the marine visibility observation codes (MVOC) included in the categories.

TABLE A1

ARTIFICIAL DATA SET

Interval 1	Interval 2	Interval 3
EHF $\leq$ 2.65	2.65 < EHF $\leq$ 4.44	EHF > 4.44
FTER $\leq$ .024	.024 < FTER $\leq$ .9	FTER > .9
RH $\leq$ 85.9	85.9 < RH $\leq$ 90.0	RH > 90.0
ASTD $\leq$ 1.02	1.02 < ASTD $\leq$ 1.91	ASTD > 1.91

Visibility Category I: MVOC 90 -> 94 (60 cases)
Visibility Category II: MVOC 95 & 96 (20 cases)
Visibility Category III: MVOC 97 -> 99 (19 cases)

II. SINGLE PREDICTOR STATISTICS

A. BIVARIATE PAIRS

Choose various visibility-predictor pairs and make bivariate plots of these pairs. This will provide immediate visual estimation of the potential predictability. As an example, let us suppose that predictor EHF of our artificial data set has 33 cases in each equally populous interval and that the visibility categories I, II and III are respectively represented by 17, 7 and 9 in interval 1; 1, 7 and 25 in interval 2; 1, 6 and 26 in interval 3. To make the bivariate plot, simply make a tabular summary of this information, as illustrated in Fig. 14. Now we define, from the bivariate plot, our coordinate system and nomenclature. Items in parentheses are examples from Fig. 14, numbers in brackets are equation numbers from Preisendorfer (1983 a,b,c) with

a letter designator indicating the paper from which it was obtained.

n = number of visibility categories ($n = 3$)

m = number of equally populous predictor intervals ($m = 3$)

j = the vertical counting index ($j = 1,\ldots,n$)

i = the horizontal counting index ($i = 1,\ldots,m$)

$n(i,j)$ = individual cell counts ($n(1,3) = 9$)

$n(.,j)$ = marginal predictand totals = $\sum_{i=1}^{m} n(i,j)$ = row totals ($n(.,2) = 20$) [3.1a]

$n(i,.)$ = marginal predictor totals = $\sum_{j=1}^{n} n(i,j)$ = column totals ($n(2,.) = 33$) [3.2a]

$n(.,.)$ = total predictand/predictor pairs = $\sum_{j=1}^{n} \sum_{i=1}^{m} n(i,j)$ = sum over all cells ($n(.,.) = 99$) [3.3a]

B. CONDITIONAL PROBABILITIES

From the bivariate pairs determine the conditional probability of visibility given a predictor. We will continue from the bivariate plot in Fig. 14, and define three probabilities:

$p_{12}(i,j)$ = $n(i,j)/n(.,.)$ = joint probability of a predictand-predictor pair occurring in a given cell = individual cell count divided by the total number of cases ($p_{12}(3,3)$ = $26/99$ = $.2626$) [3.5a]

$p_1(i)$ = $n(i,.)/n(.,.)$ = marginal probability of predictor = column total divided by the total number of cases = the column sum of the joint probabilities ($p_1(2)$ = 33/99 = .333) [3.6a]

$p_2(j)$ = $n(.,j)/n(.,.)$ = marginal probability of predictand = row total divided by the total number of cases = the row sum of the joint probabilities ($p_2(2)$ = 20/99 = .202) [3.7a]

We can now build a joint/marginal probability table as illustrated in Fig. 15, and define conditional probability.

$p_{21}(j|i)$ = $p_{12}(i,j)/p_1(i)$ = $n(i,j)/n(i,.)$ = conditional probability of predictand given a predictor = a cell's joint probability divided by the marginal probability of predictor = individual cell count divided by column total ($p_{21}(2|2)$ = .071/.333 = 7/33 = .212) [3.8a]

Now build a conditional probability table as illustrated in Fig. 16. Conditional probability of visibility, given some predictor, is the quantity of greatest interest in this study. Note that if $p_{21}(j|i) = 1/n$ for $j = 1,\ldots,n$ at some i (i.e., each cell contains 1/n of the cases in its column), then very little information is available to predict visibility at that i. However, if $p_{21}(j_0|i) = 1$ for some j_0 and $p_{21}(j|i) = 0$ for all other j values, then there is perfect predictability of class j_0 by the predictor at class i. The underlying methodology of this study will be to determine the maximum conditional probability of visibility for each predictor value.

C. STRATEGIES

Preisendorfer (1983 a,b,c) presents three different prediction strategies, two based on maximum probabilities (MAXPROB1 and MAXPROB2) and one based on natural regression.

1. Maximum Probability

This strategy consists of determining the cell, in a given column, with the highest conditional probability, and assign to the column the visibility category associated with that cell. As each column represents an interval of predictor values, we now have a visibility forecast value associated with that interval. In our example with EHF (Fig. 16), interval 1 ($i = 1$) will have a forecast value of visibility category I (VISCAT 1). Hence, if we used only EHF as a predictor, every time a value of EHF was encountered with a value ≤ 2.65, we would predict visibility category I. Similarly, for interval 2 ($i = 2$) and for interval 3 ($i = 3$) we would choose visibility category III (VISCAT 3).

MAXPROB1 and MAXPROB2 differ only in the way they handle a tie between maximal conditional probabilities in a column. Should this occur, then a decision must be made as to which predictand category will be assigned to that predictor interval. In MAXPROB1, this decision is made by a coin toss, figuratively. A random number, in the unit interval, is generated. The unit interval is divided into a number of subintervals equal to the number of tied values and each subinterval is assigned to a specific predictand

category. The subinterval into which the random number falls determines the forecast visibility category. In MAXPROB2, the lowest predictand category, among the tied categories, is chosen.

2. Natural Regression

This strategy consists of first finding the average predictand (visibility category) for each predictor interval, using conditional probabilities, and then choosing the predictand category nearest the average.

$$\bar{j}(i) = \sum_{j=1}^{n} j\, p_{21}(j|i) \qquad [7.1b]$$

Fig. 17 shows the computation for EHF interval 1 ($i = 1$). Visibility category II (VISCAT 2) would be assigned to this interval by this strategy.

D. COMPARISON STATISTICS

To determine if a predictor will be useful in forecasting, there should be a statistic with which to compare its potential utility. Preisendorfer (1983 a,b,c) defines four such statistics and their critical values. The four statistics defined are potential predictability (PP), class-error probabilities (a_0, a_1), and functional dependence (FD). Potential predictability and class-error probabilities will be defined now. Functional dependence will be addressed later.

1. Potential Predictability

Potential predictability of a predictand/predictor pair is defined as:

$$PP(2|1) = n/(n-1) \sum_{i=1}^{m} p_1(i) [\sum_{j=1}^{n} (p_{21}(j|i) - 1/n)^2]$$

$$= \sum_{i=1}^{m} p_1(i)\ PP(i)$$

where:

$$PP(i) = n/(n-1) \sum_{j=1}^{n} (p_{21}(j|i) - 1/n)^2 ,$$

$p_1(i)$ = the marginal probability of a predictor, and

$p_{21}(j|i)$ = the conditional probability of the jth predictand, given the ith predictor. [4.1a]

$PP(2|1)$ is loosely related to Shannon's definition of information [Preisendorfer, 1983a]. An example calculation is shown in Fig. 18 where EHF has a PP value of .330. To determine if this would be the best predictor using this statistic, compute the potential predictability for all predictors and rank them from highest to lowest. The predictor with the highest PP should be the best predictor for forecasting visibility using any strategy.

2. Class-Error Probabilities

Zero-class (a_0) and one-class (a_1) error probabilities can be defined to gauge the predictive skill of a prediction strategy.

$$a_0 = \sum_{i=1}^{m} p_1(i)\ p_{21}(j_0(i)|i)$$

where:

$p_1(i)$ = the marginal probability of the predictor,

$j_0(i)$ = the j_0th cell in column i assigned by the prediction strategy, and

$p_{21}(j_0(i)|i)$ = the conditional probability of the $j_0(i)$. [6.1a]

From Figs. 15 and 16, $p_1(i) = .333$ for all i; $j_0(1) = 1$, $p_{21}(j_0(1)|1) = .515$; $j_0(2) = 3$, $p_{21}(j_0(2)|2) = .758$; and $j_0(3) = 3$, $p_{21}(j_0(3)|3) = .788$. Therefore, if EHF is the only predictor,

$$a_0 = (.333)(.515) + (333)(.758) + (.333)(.788) = .686$$

The statistic a_0 is, by definition, equal to the fraction of correct forecasts in the dependent data set.

$$a_1 = \sum_{i=1}^{m} p_1(i)[p_{21}(j_0(i)+1|i) + p_{21}(j_0(i)-1|i)]$$

where:

$p_{21}(j_0(i) \pm 1|i)$ = the conditional probabilities adjacent to the $p_{21}(j_0(i)|i)$ values used in the a_0 determination.

If $j_0 = 1$ then, by definition, $p_{21}(j_0(i) - 1|i) = 0$; similarly if $j_0 = n$ then, by definition, $p_{21}(j_0(i) + 1|i) = 0$. [6.2a]
The statistic a_1 is, by definition, equal to the fraction of forecasts for which a class 1 error has been committed.
Again, from Figs. 15 and 16:

$$a_1 = (.333)(.212+0) + (.333)(.212+.0) + (.333)(.182+0)$$

$$= .202$$

To determine which one of two or more predictors is the most skillful, we can plot the (a_0, a_1) pairs on a skill diagram as in Fig. 19. The dashed lines are lines of constant class error ($CE = a_1 + 2a_2$) and the more skillful predictors will lie on the lower right part of the triangle. In general, the skill on the diagram decreases according to the zig-zag rule shown in the figure. If, for all predictors, a_1 is constant, which may occur during the first predictor determination with a data set containing relatively few poor visibility cases, then the best predictor is that one with the greatest a_0 value. In this instance there is no need to plot the pairs.

III. MULTIPLE PREDICTOR STATISTICS

Once all predictand/predictor pairs have been formed and potential predictability and skill scores determined, the predictors can be ordered by decreasing predictor skill and by potential predictability. Fig. 20 contains the bivariate plot, conditional probabilities, potential predictability and skill scores for the remaining three predictors in our artificial data set. The ordering of predictors is shown in Table A2. Therefore, EHF would be chosen as our first predictor, as illustrated on the skill diagram in Fig. 19. As RH, FTER and ASTD have equal a_0 and a_1 values, they are ranked according to decreasing potential predictability.

TABLE A2

RANKING OF PREDICTORS BY SKILL AND POTENTIAL PREDICTABILITY

		a_0	a_1	PP
1st	EHF	.686	.202	.330
2nd	RH	.606	.202	.225
3rd	FTER	.606	.202	.211
4th	ASTD	.606	.202	.209

Preisendorfer (1983b) develops statistics, similar to those already mentioned, for multiple predictors. The main conceptual difficulty of additional predictors is the increase of dimensions. One predictor presents a relatively

simple two-dimensional problem (predictor 1 vs. predictand); two predictors present a three-dimensional problem (predictor 1 vs. predictor 2 vs. predictand); three or more predictors present four-dimensional and larger problems. However, with a little manipulation, all of the multi-dimensional problems greater than two-dimensions can be reduced to a two-dimensional problem. This is illustrated in Figs. 21 and 22 for three-dimensions (two predictors) and four-dimensions (three predictors). An easily programmable equation can be developed to create these two-dimensional arrays based upon the number of equally populous intervals for each predictor and upon the interval in which a particular data case resides.

In our continuing example, reduce the equally populous intervals for each predictor to an integer number ($i = 1,\ldots,m$) with 1 corresponding to the lowest interval and m corresponding to the highest interval, as defined for the predictor index in Section II.A. Let

ii = the interval integer number for EHF,

jj = the interval integer number for RH,

kk = the interval integer number for FTER,

mm = the interval integer number for ASTD,

ll = the column location in the two-dimensional bivariate plot (equivalent to i for a single predictor),

IGP1 = the total number of intervals for EHF,

IGP2 = the total number of intervals for RH,

IGP3 = the total number of intervals for FTER,

IGP4 = the total number of intervals for ASTD.

Then, for one predictor, EFH:

$$ll = ii$$

for two predictors, EHF and RH:

$$ll = IGP2(ii-1) + jj$$

for three predictors, EHF, RH and FTER:

$$ll = IGP2(ii-1+IGP1(kk-1)) + jj$$

for four predictors, EHF, RH, FTER and ASTD:

$$ll = IGP2(ii-1+IGP1(kk-1+IGP3(mm-1))) + jj$$

This equation form can be expanded to accommodate any number of predictors.

IV. FUNCTIONAL DEPENDENCE

After the first predictor has been selected, either from its skill score or potential predictability, we need a means to determine whether or not to add a new predictor to the one(s) already chosen. For this purpose, Preisendorfer (1983c) proposes a functional dependence index (FD) which describes the dependence of the new predictor being considered upon those already in the set of predictors. If FD is large

(on the scale 0 to 1) then it can be represented by predictors already chosen and its inclusion into the set of predictors would be redundant. However, if FD is small (on the scale 0 to 1) then it is likely to be a useful addition to the existing collection of predictors.

$$FD(2|1) = m/2(m-1) \sum_{i=1}^{m} \sum_{j=1}^{n} p_{12}(i,j)|q(i,j)-r(i,j)| \qquad (2.1c)$$

where:

$$q(i,j) = \sum_{k=1}^{n-j} p_{21}(j+k|i+1) + \sum_{k=1}^{j-1} p_{21}(j-k|i-1) \qquad (2.2c)$$

= the sum of the conditional probabilities which lie in column i+1 and rows greater than j and the conditional probabilities which lie in column i-1 and rows less than j

= the sum of the conditional probabilities to the right and up, and to the left and down. The upper left (1,n) and lower right (m,1) cells will always have q values equal to zero.

$$r(i,j) = \sum_{k=1}^{j-1} p_{21}(j-k|i+1) + \sum_{k=1}^{n-j} p_{21}(j+k|i-1) \qquad (2.3c)$$

= the sum of the conditional probabilities which lie in column i+1 and rows less than j and the conditional probabilities which lie in column i-1 and rows greater than j

= the sum of the conditional probabilities to the right and down, and to the left and up. The upper right (m,n) and lower left (1,1) cells will always have r values equal to zero.

$p_{12}(i,j)$ and $p_{21}(j \pm k | i \pm 1)$ = the joint and conditional probabilities defined earlier, differing only in that the abscissa and ordinate are now predictor vs. predictor vice predictor vs. visibility.

Fig. 23 illustrates the FD computation for RH given EHF. In this example, $FD(2|1) = FD(RH|EHF) = .286$.

V. CRITICAL VALUES

Once the various statistics have been found, a means to determine whether they are significant must be established. Preisendorfer (1983 a,b,c) proposes the use of Monte Carlo means, applied as follows.

From the bivariate plot, as in Figs. 14, 21b and 22b, we determine the marginal probabilities of the predictor ($p_1(i)$) and establish incremental values from 0 to 1 (note that for equally populous predictor intervals, $p_1(i) = 1/m$, a constant, where m = the number of intervals). We then cast a total of $n(.,.)$ randomly generated numbers into the intervals to simulate a new data set. After each randomly generated data case is cast into a column, it is placed into a cell using uniform probability. Fig. 24 shows the incremental values associated with the bivariate plot in Fig. 21b. In our continuing example we have $n(.,.) = 99$, so we would generate 99 random numbers in the unit interval. All random numbers $\leq .071$ would be placed in column $i = 1$; those greater

than .071 and $\leq$ .192 would be placed in column i = 2; and so on. As each data case is placed into a column, a single random number is generated to determine into which cell the case is to be placed (e.g., a random number $\leq$ .33 would be counted in cell (i,1); a random number greater than .33 and $\leq$ .66 would be counted in cell (i,2); etc.). After all 99 cases have been cast into their appropriate cells, all of the statistics previously discussed would be computed and saved. This process would be repeated 100 times so that we would have an array containing 100 randomly generated potential predictabilities, a_0's, a_1's and FD's. These would be sorted from lowest to highest and the 96th (PP(96), $a_0(96)$, $a_1(96)$ and FD(96)) value would determine the upper 5% critical value and the 5th (PP(05), $a_0(05)$, $a_1(05)$ and FD(05)) value would determine the lower 5% critical value. For all statistics other than FD, we want values from our dependent data set to be greater than the upper 5% or less than the lower 5% critical values. For FD we want values lower than the upper 5% critical value to ensure that our second, and subsequent, predictor is not significantly dependent on the previous predictor(s).

VI. CHOOSING PREDICTORS

The first predictor is determined as shown in Section III. That is, by computing initial PP, a_0 and a_1 values for each predictor, ordering them by skill score and PP and choosing

the one with the greater skill score, or greatest PP in the event that all skill scores are identical.

Subsequent predictors will be subjected to two tests; functional dependence and skill score. Let

p = the number of predictors already chosen,

$a_0(k-1)$ and $a_1(k-1)$ = the 0- and 1-class errors of the previous stage of construction of the developmental model,

k = the index of the current stage.

Then, for the next (kth) predictor to be accepted it should meet the following three conditions:

(1) $FD < FD(96|i) \quad (i = 1,p)$

(2) $a_0(k) > a_0(k-1)$ and $a_1(k) \leq a_1(k-1)$

(3) $a_0(k) \geq a_0(96)$ and $a_1(k) \leq a_1(05)$

If condition (1) is not met but conditions (2) and (3) are, then a predictor may still be used, but the increase of predictability of the predictand will, on average, be less than if condition(1) had been met. However, if conditions (2) and (3) are not met, then the predictor should not be considered further. Repeat this process at all stages for all remaining predictors until no further predictors are available, then stop the construction of the developmental model.

VII. TESTING THE DEVELOPMENTAL MODEL ON INDEPENDENT DATA

Once the model has been developed and no further predictors remain to be considered, we can test it for skills (a_0, a_1) on an independent data set (any set whose numbers were not used to develop the model). This is easily accomplished by sorting the independent data case values into predictor intervals, determined from the dependent data, and calculating the location in the forecast array (11 in Figs. 21b and 22b) of the appropriate prediction, using the equations established in Section III. It is to be expected that on average the test (a_0, a_1) points on the skill diagram, for an independent data set, will not be as skillful as on the set of developmental points.

APPENDIX B

LINEAR REGRESSION AND THRESHOLD MODELS

A. LINEAR REGRESSION

In this study a least-squares, multiple linear regression model, known as BMDP2R in the BMDP Statistical Software [University of California, 1981], was used. The procedure used is called forward step-wise selection and picks the predictors (of the many offered) that have the highest correlation with the predictand (visibility) based upon F-to-enter and F-to-remove limits, where F is a ratio which tests the significance of the coefficients of the predictors in the regression equation.

The regression model fitted to the data is

$$y = a + b_1x_1 + b_2x_2 + \ldots + b_px_p + \varepsilon$$

where:

y = the dependent variable (predictand) which can be either a continuous function or a discrete value

$x_1,\ldots,x_p$ = the independent variables (predictors)

$b_1,\ldots,b_p$ = the regression coefficients

a = the intercept

p = the number of independent variables

ε = the error with mean zero.

The predicted value $\hat{y}$, and the general form of the resulting equation, is

$$\hat{y} = a + b_1x_1 + b_2x_2 + \ldots + b_px_p$$

The step-wise selection of predictors continues until there are no predictors remaining which meet the F-to-enter criteria. The regression equation generated at each step is printed, along with its R-value (the correlation of the dependent variable y with the predicted value $\hat{y}$) and R^2. The resulting set of equations, one for each step, are reviewed, and that equation containing only those predictors which increased R^2 by at least .01 is retained for application.

The role of regression, once appropriate predictor variables have been selected, is simply that of dimension reduction (representing a multivariate structure by a univariate proxy which constitutes a classificatory or predictive index). This proxy takes the form of a polynomial, linear in its coefficients, of the components of the multivariate structure. The problem now becomes one of determining the form of the state conditional distributions (one for each group of interest; e.g., 1, 2 and 3 for visibility categories I, II and III, as used in this study). Once an appropriate form has been selected, it remains, then, to determine the parameters of the class conditional distributions (e.g., means and variances) and then apply the decision criteria or threshold model.

B. THRESHOLDS [LOWE, 1984a]

1. Notation

$E \equiv$ an event; this is an indicator variable which when $E = 1$, the threatening event occurs, and when $E = 0$, the non-threatening event occurs.

$C \equiv$ the classification of an unknown event which when $C = 1$, the event is classified as a threat, and when $C = 0$, the event is classified as a non-threat.

$P[E = 1] \equiv$ unconditional probability of occurrence of threat.

$P[E = 0] \equiv$ unconditional probability of occurrence of non-threat.

Error of the 1st kind (false alarm) $[C=1 \cap E=0]$.

Error of the 2nd kind (miss) $[C=0 \cap E=1]$.

$P[C=1 \cap E=0] \equiv$ joint probability of an error of the 1st kind.

$P[C=0 \cap E=1] \equiv$ joint probability of an error of the 2nd kind.

$P[C=1|E=0] \equiv$ class conditional probability of misclassifying a non-threat.

$P[C=0|E=1] \equiv$ class conditional probability of misclassifying a threat.

$$P[C=1 \cap E=0] = P[C=1|E=0]\ P[E=0].$$

$$P[C=0 \cap E=1] = P[C=0|E=1]\ P[E=0].$$

$z =$ a value of the predictive index (equivalent to $\hat{y}$, above).

$Z =$ range of the predictive index on the real line.

For a dichotomous problem, Z is into two parts Z_0, Z_1,

$$C = 0 \text{ if } z \in Z_0$$

$$C = 1 \text{ if } z \in Z_1$$

The decision regions are mutually exclusive and exhaustive (i.e., $Z_0 \cap Z_1 = 0$ and $Z = Z_0 \cup Z_1$).

Thresholds $\equiv$ boundary(s) between decision regions.

$p(z|E=0)$ $\equiv$ class conditional density of z given that E = 0.

$p(z|E=1)$ $\equiv$ class conditional density of z given that E = 1.

$\Lambda(z) = p(z|E=1)/p(z|E=0)$ = the maximum likelihood ratio (i.e., the ratio of class conditional densities).

$p_e = p\{[C=1 \cap E=0] \cup [C=0 \cap E=1]\}$ = the total probability of error.

2. <u>Minimum Probability of Error Criterion</u>

p_e = probability of an incorrect classification.

$$p_e = p[C=1|E=0]\ p[E=0] + p[C=0|E=1]\ p[E=1]$$

where $p[E=1] + p[E=0] = 1$. Note that the events E = 1 and E = 0 are mutually exclusive and exhaustive. The objective is to select decision regions (thresholds) so as to minimize p_e.

$p[C=0|E=1] = \int_{z \in Z_0} p(z|E=1)\,dz$ = the probability of misclassifying E = 1.

$$p[C=0|E=1] = \int_{z \in Z_0} p(z|E=1)\,dz + \int_{z \in Z_1} p(z|E=1)\,dz - \int_{z \in Z_1} p(z|E=1)\,dz$$

$$p[C=0|E=1] = 1 - \int_{z \in Z_1} p(z|E=1)dz$$

$$p[C=1|E=0] = \int_{z \in Z_1} p(z|E=0)dz$$

these are substituted into the expression for p_e

then,

$$p_e = p[E=0] \int_{z \in Z_1} p(z|E=0)dz + p[E=1][1 - \int_{z \in Z_1} p(z \mid E=1)dz]$$

and algebraic rearrangement yields,

$$p_e = p[E=1] - \int_{z \in Z_1} \{p[E=0]\ p(z|E=0) - p[E=1]\ p(z|E=1)\}dz$$

In order to minimize p_e, Z_1 (the decision region for C = 1) will include all those values of z for which the integrand in the expression for p_e will be negative. The decision regions can be symbolically represented as follows:

$$Z_0 = \{z: p[E=0]\ p(z|E=0) - p[E=1]\ p(z|E=1) > 0\}$$

$$Z_1 = \{z: p[E=0]\ p(z|E=0) - p[E=1]\ p(z|E=1) < 0\}$$

An alternative representation is given by,

$$Z_0 = \{z: p[E=0]\ p(z|E=0) > p[E=1]\ p(z|E=1)\}$$

$$= \{z: p[E=0]/p[E=1] > p(z|E=1)/p(z|E=0)\}$$

Likewise,

$$Z_1 = \{z: p[E=0]/p[E=1] < p(z|E=1)/p(z|E=0)\}$$

These statements can be combined to give,

$$p(z|E=1)/p(z|E=0) = \Lambda(z) \underset{c=0}{\overset{c=1}{\gtrless}} p[E=0]/p[E=1]$$

Thresholds are the value(s) of z for which

$$\Lambda(z) = p[E=0]/p[E=1]$$

This equation can be solved for z either analytically or numerically depending on the forms of the density functions.

3. Threshold Cases

In order to examplify the model, the assumption is made that the class conditional distributions are Gaussian. There are essentially three distinct cases that can arise.

a. Case I: Equal variances; different means (Referred to as the equal variance model in the text)

$$p(z|E=1) = k \exp\{(-1/2)(z-\mu_1)^2/\sigma^2\}$$

$$p(z|E=0) = k \exp\{(-1/2)(z-\mu_0)^2/\sigma^2\}$$

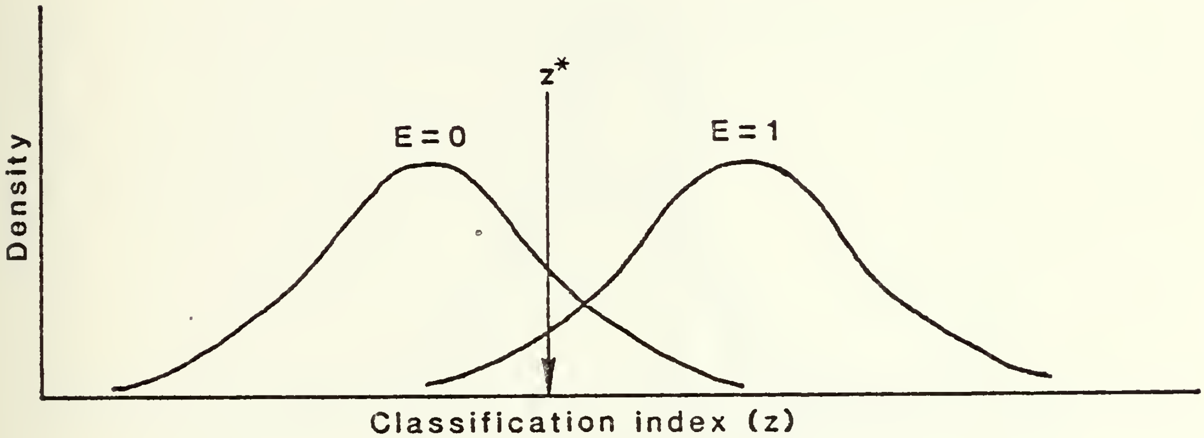
where:

$$k = (2\pi)^{-1/2}\sigma^{-1} .$$

$$\Lambda(z) = \frac{\exp\{(-1/2)(z-\mu_1)^2/\sigma^2\}}{\exp\{(-1/2)(z-\mu_0)^2/\sigma^2\}} \begin{matrix} c=1 \\ > \\ < \\ c=0 \end{matrix} \frac{p_0}{p_1}$$

where $p_0 = p[E=0]$ and $p_1 = p[E=1]$. Thus, the threshold value is

$$z^* = (\mu_0 + \mu_1)/2 + \sigma^2 \ln(p_0/p_1)/(\mu_1 - \mu_0)$$



The position of the threshold depends on the relative values of p_1 and p_0. The threshold moves toward the group with the smallest p_i. If $p_1 = p_0$ the threshold will be the value of z where the densities intersect (i.e., where the densities are equal).

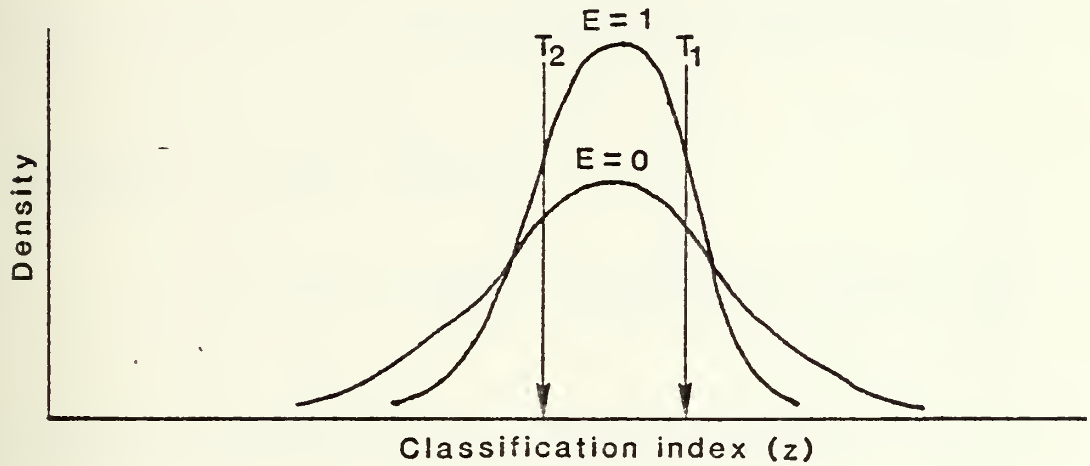
b. Case II: Equal means; different variances

$$\Lambda(z) = \frac{\sigma_0 \exp\{(-1/2)(z-\mu_1)^2/\sigma_1^2\}}{\sigma_1 \exp\{(-1/2)(z-\mu_0)^2/\sigma_0^2\}} \begin{matrix} c=1 \\ > \\ < \\ c=0 \end{matrix} \frac{p_0}{p_1}$$

with the threshold

$$Z^* = \pm \left[\frac{2\sigma_0^2\sigma_1^2}{(\sigma_1^2-\sigma_0^2)} \ln \left(\frac{p_0\sigma_1}{p_1\sigma_0}\right) \right]^{1/2}$$

Note that in this situation there are two thresholds. The group having the smaller variance will lie between the two thresholds.



The thresholds shown are typical of a situation where $p_1 < p_0$. Note that these thresholds lie between the two intersections of the densities. If the inequality of prior probabilities were reversed, the thresholds would lie outside of the region between the two density intersections. Further note that the decision region for the group having the lesser variance lies between the thresholds.

c. Case III: General Solution (Referred to as the Quadratic Model in the text)

$$p(z|E=1) = k/\sigma_1 \exp\{(-1/2)(z-\mu_1)^2/\sigma_1^2\}$$

$$p(z|E=0) = k/\sigma_0 \exp\{(-1/2)(z-\mu_0)^2/\sigma_0^2\}$$

$$\Lambda(z) = \exp\{1/2 \left[\left(\frac{z-\mu_0}{\sigma_0}\right)^2 - \left(\frac{z-\mu_1}{\sigma_1}\right)^2 \right]\} \underset{c=0}{\overset{c=1}{\gtrless}} \frac{p_0\sigma_1}{p_1\sigma_0}$$

where $k = (2\pi)^{-1/2}$. Algebraic manipulation produces

$$(\sigma_1^2 - \sigma_0^2)z^2 + 2(\sigma_0^2\mu_1 - \sigma_1^2\mu_0)z$$

$$+ [(\sigma_1^2\mu_0^2 - \sigma_0^2\mu_1^2) - 2\sigma_0^2\sigma_1^2 \ln(p_0\sigma_1/p_1\sigma_0)] \underset{c=1}{\overset{c=1}{\gtrless}}$$

which is recognizable as a quadratic equation in z.

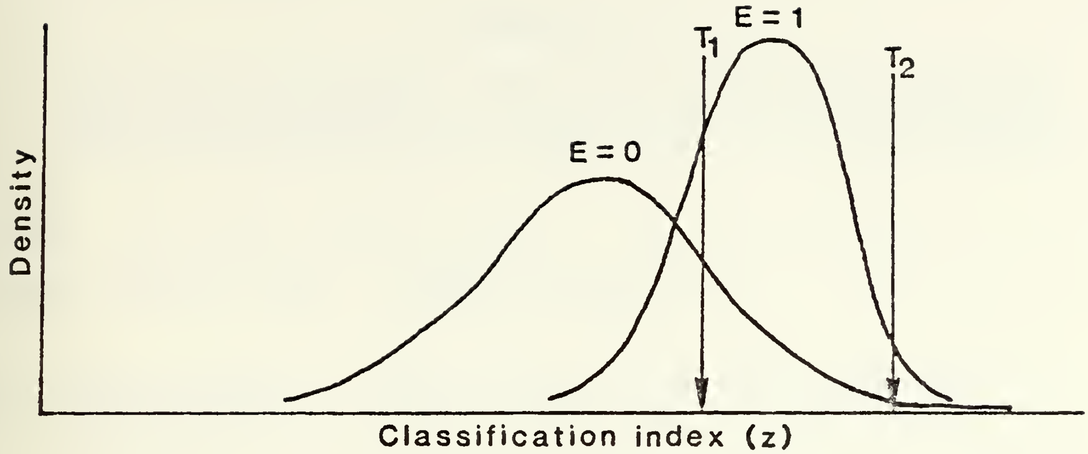
$$z^* = -b \pm (b^2 - 4ac)^{1/2}/2a$$

where:

$$a = \sigma_1^2 - \sigma_0^2$$

$$b = 2(\sigma_0^2\mu_1 - \sigma_1^2\mu_0)$$

$$c = (\sigma_1^2\mu_0^2 - \sigma_0^2\mu_1^2) - 2\sigma_1^2\mu_0^2 \ln(p_0\sigma_1/p_1\sigma_0)$$



The remarks given for the figures in cases I and II are also applicable here. More often than not, only one of a pair of thresholds induced by differing variances will be of real interest. If the variances of the two groups are radically different, then both members of the threshold pair become important.

In the foregoing, normal class conditional distributions were assumed. This was done because the Gaussian form admits of a rather clean analytical solution. However, the general concept of the minimum probable error decision criteria may be applied to any form of density function. Indeed, the density function of one group need not even be the same form as that for another group (one might be exponential and the other Gaussian). The difficulty with most non-Gaussian forms is that they seldom admit of closed analytical forms and require numerical means in determination of thresholds.

APPENDIX C

NORTHERN HEMISPHERE PREDICTOR PARAMETERS AVAILABLE FOR THE NORTH PACIFIC OCEAN, JULY 1979, EXPERIMENTS

Area: 30°-60°N; 145°E-130°W

Model output time: 0000GMT (TAU00)

A.

Model output parameters	Descriptive name of parameters
Primitive equation model	
TX	Surface air temperature
EX	Surface vapor pressure
EHF	Evaporative heat flux
SEHF	Sensible plus Evaporative heat flux
THF	Total heat flux
H510	1000-500 mb thickness anomaly
GGTHTA	Surface-front location parameter
FTER	Advective fog probability
Mass structure model	
PS	Surface pressure
TAIR	Surface air temperature
EAIR	Surface vapor pressure
TSEA	Sea surface temperature
SSANOM	Sea surface temperature anomaly
T925	925 mb temperature
U925	925 mb zonal wind component
V925	925 mb meridional wind component
NCLOUD	Total cloud cover
Marine wind model	
VVWW	Marine surface wind speed
DDWW	Marine surface wind direction

B. Climatological parameter

CLIMO	National Climatic Center fog frequency climatology

C. Derived parameters

ASTD	TAIR-TSEA
RH	Surface relative humidity

APPENDIX D

NOGAPS PREDICTOR PARAMETERS AVAILABLE FOR THE NORTH ATLANTIC OCEAN, 15 MAY-15 JULY 1983, EXPERIMENTS

Area: Entire North Atlantic Ocean and Mediterranean Sea

Model output time: 1200GMT (TAU00)

A.

Model output parameter	Descriptive name of parameter
D1000	1000 mb geopotential height
D925	925 mb geopotential height
D850	850 mb geopotential height
D700	700 mb geopotential height
D500	500 mb geopotential height
D400 *	400 mb geopotential height
D300 *	300 mb geopotential height
D250 *	250 mb geopotential height
TAIR	Surface air temperature
T1000	1000 mb temperature
T925	925 mb temperature
T700	700 mb temperature
T500	500 mb temperature
T400 *	400 mb temperature
T300 *	300 mb temperature
T250 *	250 mb temperature
EAIR	Surface vapor pressure
E1000	1000 mb vapor pressure
E925	925 mb vapor pressure
E850	850 mb vapor pressure
E700	700 mb vapor pressure
E500	500 mb vapor pressure
UBLW	Boundary layer zonal wind component
U1000	1000 mb zonal wind component
U925	925 mb zonal wind component

U850	850 mb zonal wind component
U700	700 mb zonal wind component
U500	500 mb zonal wind component
U400 *	400 mb zonal wind component
U300 *	300 mb zonal wind component
U250 *	250 mb zonal wind component
VBLW	Boundary layer meridional wind component
V1000	1000 mb meridional wind component
V925	925 mb meridional wind component
V850	850 mb meridional wind component
V700	700 mb meridional wind component
V500	500 mb meridional wind component
V400 *	400 mb meridional wind component
V300 *	300 mb meridional wind component
V250 *	250 mb meridional wind component
VOR925 **	925 mb vorticity
VOR500 **	500 mb vorticity
PS	Surface pressure
SMF	Surface moisture flux
PBLD	Planetary boundary-layer depth
STRTFQ	Percent stratus frequency
STRTTH	Stratus thickness
SHF	Surface heat flux
ENTRN	Entrainment at top of marine boundary-layer
DRAG **	Drag coefficient (C_D)

B. <u>Derived parameters</u>

DTDP	Vertical gradient of temperature
DEDP	Vertical gradient of vapor pressure
DUDP	Vertical gradient of zonal wind
DVDP	Vertical gradient of meridional wind
RH	Surface relative humidity
BM1 ***	$2.81132 + (.16201 \times \text{EAIR}) - (.00237 \times \text{E850}) - (.0739 \times \text{T925}) - (.16179 \times \text{E925})$

BM2	***	$2.08302 + (.36810 \times TAIR) - (.26675 \times T1000) - (.15980 \times T925)$
BM3	***	$3.00866 + (.11771 \times EAIR) - (.01024 \times E850) - (.19321 \times E925)$
BM4	***	$2.42235 - (.000418 \times UBLW) + (.000255 \times U700)$
BM5	***	$2.55859 - (.000355 \times V1000)$
BM6	***	$2.57317 + (.000893 \times D1000) - (.0000489 \times D700)$
BM7	***	$-15.2173 + (.01764 \times PS) - (.01007 \times STRTFQ) + (.02642 \times STRTTH) + (.06042 \times SHF)$

* Parameters which were not used due to their being considered as having little likelihood of being important in forecasting marine visibility.

** Parameters which were not used due to loss of significant digits during transfer from tape to mass storage.

*** Linear regression equation parameters.

APPENDIX E

SKILL AND THREAT SCORES

FORECAST	3	R	S	T
	2	U	V	W
	1	X	Y	Z
		1	2	3
		OBSERVED		

Total = R + S + T + U + V + W + X + Y + Z

P1 = (R+U+X)/Total   P3 = (T+W+Z)/Total

P2 = (S+V+Y)/Total   PN = greatest of P1, P2 or P3

Raw scores

A0 = % correct = (X+V+T)/Total

A1 = 1 - class error = (U+S+Y+W)/Total

TS1 = Threat score for visibility category I
= X/(R+U+X+Y+Z)

TS2 = Threat score for visibility category II
= V/(U+X+V+Y+W)

TS12 = Threat score for visibility categories I and II
= (X+V)/(Total-T)

TS12 is designed to represent the skill of forecasting visibility categories I and II as separate categories, rather than their skill as a combined category, which would be (U+V+X+Y)/(Total-T).

Adjusted scores

$$AA0 = (A0-PN)/(1-PN)$$

$$ATS1 = (TS1-P1)/(1-P1)$$

$$ATS2 = (TS2-P2)/(1-P2)$$

$$ATS12 = (TS12-[P1+P2])/(1-[P1+P2])$$

APPENDIX F

TABLES

TABLE I. A SUMMARY OF THE OBSERVATIONS (PERCENTAGE FREQUENCIES) OF THREE VISIBILITY CATEGORIES (VISCAT'S), FOR THE NORTH ATLANTIC OCEAN HOMOGENEOUS AREAS SHOWN IN FIG. 1, 15 MAY-15 JULY 1983

AREA	NUMBER OF OBERSERVATIONS	VISCAT I	VISCAT II	VISCAT III
1	2725	163 (.06)	436 (.16)	2126 (.78)
2	2867	277 (.10)	317 (.11)	2273 (.79)
3E	131	8 (.06)	31 (.24)	92 (.70)
3W	2288	437 (.19)	284 (.12)	1567 (.68)
4	4771	129 (.03)	597 (.13)	4045 (.85)
5E	1087	9 (.01)	94 (.09)	984 (.91)
5W	2307	8 (.003)	40 (.02)	2259 (.98)
6N	580	19 (.03)	45 (.08)	516 (.89)
6M	2337	21 (.01)	131 (.06)	2185 (.93)
6S	60	1 (.02)	2 (.03)	57 (.95)
7	801	7 (.01)	34 (.04)	760 (.95)
8	1284	1 (.001)	27 (.02)	1256 (.98)
ENTIRE NORTH ATLANTIC AND MEDITERRANEAN	21,238	1080 (.05)	2038 (.10)	18,120 (.85)

TABLE II. NUMBER OF OBSERVATIONS (PERCENTAGE FREQUENCIES) OF THREE VISIBILITY CATEGORIES (VISCAT'S), AND 95% CONFIDENCE INTERVALS FOR THE DEPENDENT AND INDEPENDENT DATA, FOR THE NORTH PACIFIC OCEAN AND AREA 3W OF THE NORTH ATLANTIC OCEAN

North Pacific Ocean, July 1979

	VISCAT I	VISCAT II	VISCAT III	TOTAL # OF OBSERVATIONS
95% CI	.207-.229	.126-.144	.635-.660	
Dependent data	816 (.222)	498 (.135)	2368 (.643)	3682
Independent data	388 (.211)	246 (.134)	1207 (.656)	1841
Total	1204 (.218)	744 (.135)	3575 (.647)	5523

North Atlantic Ocean area 3W, FATJUN 1983

	VISCAT I	VISCAT II	VISCAT III	TOTAL # OF OBSERVATIONS
95% CI	.175-.207	.111-.138	.666-.704	
Dependent data	296 (.194)	190 (.125)	1040 (.682)	1526
Independent data	141 (.185)	94 (.123)	527 (.692)	762
Total	437 (.191)	284 (.124)	1567 (.685)	2288

TABLE III. THE INITIAL FIVE BEST PREDICTORS FOR EPI'S OF FOUR THROUGH TEN, FOR EACH STRATEGY, WITH ASSOCIATED PP, a_0, a_1 AND CE VALUES FROM THE NORTH PACIFIC OCEAN DEPENDENT DATA, JULY 1979

			Maximum-probability			Natural-regression		
EPI	Predictor	PP	a_0	a_1	CE	a_0	a_1	CE
4	EHF	.328	.684	.135	.497	.491	.467	.551
	SEHF	.315	.681	.135	.503	.478	.475	.569
	FTER	.317	.680	.135	.505	.482	.468	.568
	CLIMO	.296	.657	.135	.551	.471	.478	.580
	RH	.311	.649	.135	.567	.508	.442	.542
5	EHF	.337	.697	.135	.471	.435	.538	.592
	SEHF	.319	.688	.135	.489	.535	.400	.530
	FTER	.314	.678	.135	.509	.539	.396	.526
	RH	.312	.658	.135	.549	.449	.518	.584
	CLIMO	.295	.658	.135	.549	.418	.549	.615
6	EHF	.338	.695	.135	.475	.491	.467	.551
	SEHF	.319	.690	.135	.485	.478	.475	.569
	FTER	.318	.673	.135	.519	.574	.349	.503
	RH	.316	.661	.135	.543	.508	.442	.542
	CLIMO	.295	.659	.135	.547	.471	.478	.580
7	EHF	.337	.693	.135	.479	.529	.415	.527
	SEHF	.319	.685	.135	.495	.523	.417	.537
	FTER	.320	.675	.135	.515	.523	.417	.537
	CLIMO	.297	.661	.135	.543	.435	.528	.602
	RH	.314	.659	.135	.547	.308	.654	.730
8	EHF	.338	.688	.135	.489	.491	.467	.551
	SEHF	.320	.681	.135	.503	.478	.475	.569
	FTER	.320	.680	.135	.505	.553	.377	.517
	CLIMO	.301	.663	.135	.539	.404	.567	.625
	RH	.315	.657	.135	.551	.508	.441	.543

TABLE III (CONT.)

9	EHF	.340	.693	.135	.479	.522	.425	.531
	SEHF	.322	.686	.135	.493	.514	.429	.543
	FTER	.324	.683	.135	.499	.574	.349	.503
	CLIMO	.299	.663	.135	.539	.443	.516	.598
	RH	.315	.657	.135	.551	.476	.482	.566
10	EFH	.341	.696	.135	.473	.491	.467	.551
	SEHF	.323	.688	.135	.489	.534	.401	.531
	FTER	.322	.678	.135	.509	.539	.396	.526
	CLIMO	.300	.662	.135	.541	.418	.549	.615
	RH	.316	.658	.135	.549	.508	.441	.543

TABLE IV. FIRST-STAGE CONTINGENCY TABLE STATISTICS A0, TS1, AA0 AND ATS1 FOR BOTH DEPENDENT AND INDEPENDENT NORTH PACIFIC OCEAN, JULY 1979, DATA, FOR EPI'S OF FOUR THROUGH TEN AND THE MAXIMUM-PROBABILITY STRATEGY, WITH EHF AS THE FIRST PREDICTOR FOR EACH NUMBER OF EPI'S

	Dependent data				Independent data			
EPI	A0	TS1	AA0	ATS1	A0	TS1	AA0	ATS1
4	.684	.36	.113	.17	.686	.34	.087	.16
5	.697	.35	.150	.17	.695	.33	.114	.15
6	.695	.32	.145	.13	.696	.30	.117	.12
7	.693	.30	.139	.10	.693	.28	.107	.09
8	.688	.27	.126	.06	.694	.27	.110	.08
9	.693	.36	.139	.17	.695	.34	.114	.16
10	.696	.35	.149	.17	.695	.33	.114	.15

TABLE V. FD(96), FD, RSS FD AND a_0 FOR STRATEGY MAXPROB2, NORTH PACIFIC OCEAN, JULY 1979, DEPENDENT DATA, FOR THOSE PREDICTORS SELECTED AT EACH STAGE OF THE DEVELOPMENTAL MODEL USING FIVE EPI'S. FD(96) IS COMPUTED FROM 100 RANDOMLY GENERATED DATA SETS, AS EXPLAINED IN APPENDIX A, AND PROVIDES A MEASURE OF HOW MUCH ADDITIONAL PREDICTABILITY MAY BE EXPECTED FROM THE INCLUSION OF A NEW PREDICTOR. IDEALLY, RSS FD SHOULD BE LESS THAN FD(96)

		FD, of predictor added, on					
Predictor added	FD(96)	EHF	DDWW	H510	RH	RSS FD	a_0
EHF	-	-	-	-	-	-	.697
DDWW	.1399	.1494	-	-	-	.1494	.699
H510	.1978	.2488	.2185	-	-	.3311	.704
RH	.2423	.2606	.2087	.1515	-	.3666	.746
THF	.2798	.3290	.1464	.1678	.1907	.4408	.820
CLIMO	.3128	.3558	.1727	.1823	.2551	*	.882

*RSS FD was not computed for CLIMO as the choice for the sixth predictor was between only CLIMO and SEHF. It was more economical to compute contingency table statistics for each and to choose the best predictor from those results.

TABLE VI. CONTINGENCY TABLES AND RELATED STATISTICS FOR BOTH DEPENDENT (3682 OBSERVATIONS) AND INDEPENDENT (1841 OBSERVATIONS) NORTH PACIFIC OCEAN, JULY 1979, DATA, FROM STAGE FOUR OF THE DEVELOPMENTAL MODEL. PREDICTORS ARE EHF, DDWW, H510 AND RH, EACH DIVIDED INTO FIVE EPI'S, FOR (A) MAXPROB1, (B) MAXPROB2 AND (C) NATURAL-REGRESSION

(a) MAXPROB1

DEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	316	301	2198
2	29	79	29
1	471	118	141

AO = .75 AAO = .29

A1 = .13

TS1 = .44 ATS1 = .28

TS2 = .14 ATS2 = .01

TS12 = .37 ATS12 = .02

INDEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	175	162	1065
2	24	26	35
1	189	58	107

AO = .70 AAO = .12

A1 = .15

TS1 = .34 ATS1 = .17

TS2 = .09 ATS2 = -.06

TS12 = .28 ATS12 = -.10

TABLE VI (CONT.)

(b) MAXPROB2

DEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	228	238	2077
2	25	108	63
1	563	152	228

AO =	.75	AAO =	.29
A1 =	.13		
TS1 =	.47	ATS1 =	.32
TS2 =	.18	ATS2 =	.06
TS12 =	.42	ATS12 =	.10

INDEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	135	136	1007
2	23	29	48
1	230	81	152

AO =	.69	AAO =	.09
A1 =	.16		
TS1 =	.37	ATS1 =	.20
TS2 =	.09	ATS2 =	-.05
TS12 =	.31	ATS12 =	-.05

TABLE VI (CONT.)

(c) Natural-Regression

DEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	75	171	1773
2	501	279	565
1	240	48	30

AO = .62 AAO = -.06

A1 = .35

TS1 = .27 ATS1 = .06

TS2 = .18 ATS2 = .05

TS12 = .27 ATS12 = -.13

INDEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	72	91	857
2	226	128	298
1	90	27	52

AO = .58 AAO = -.21

A1 = .35

TS1 = .19 ATS1 = -.02

TS2 = .17 ATS2 = .04

TS12 = .22 ATS12 = -.19

TABLE VII. LINEAR-REGRESSION EQUATION FOR THE PREDICTED VALUE OF THE VISIBILITY CATEGORY ($\hat{Y}$), $\hat{Y}$ STATISTICS WITH RESPECT TO THE ACTUAL VISIBILITY CATEGORIES (Y) AND THRESHOLD VALUES FROM THE EQUAL-VARIANCE ASSUMPTION MODEL, NORTH PACIFIC OCEAN, JULY 1979. NOTATION IS AS IN APPENDIX B.

$$\hat{y} = 3.78586 + .04118(\mathrm{EHF}) - .91412(\mathrm{FTER}) - .01592(\mathrm{RH})$$

Class conditional distributions (i.e., distribution of $\hat{y}$ for a given y).

y	Number of observations of y	Frequency of y (p)	Mean Value of $\hat{y}$ (m)	Standard deviation of $\hat{y}$ (σ)
1	816	.222	2.077 (m_1)	.348
2	498	.135	2.263 (m_2)	.382
3	2368	.643	2.568 (m_3)	.353

T_1 = threshold between y = 1 and y = 2 = 2.506

T_2 = threshold between y = 2 and y = 3 = 1.768

T_3 = threshold between y = 1 and y = 3 = 2.048

State conditional distributions for visibility category I (y = 1), II (y = 2) and III (y = 3) depicting threshold values and means.

TABLE VII (CONT.)

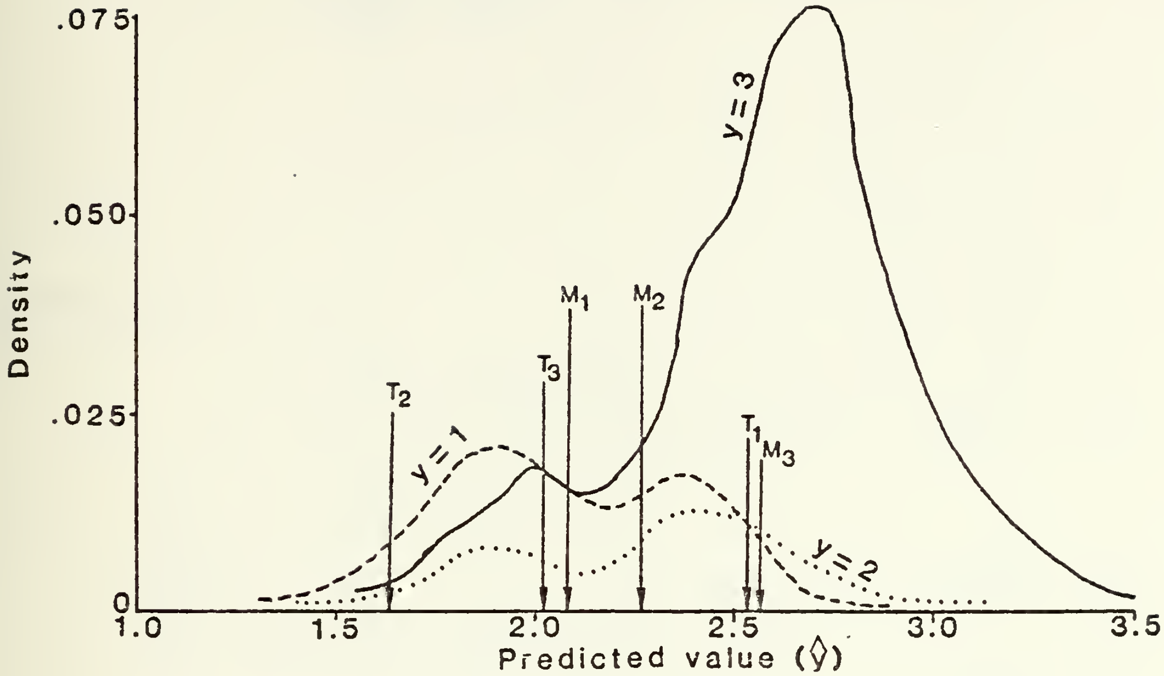


TABLE VIII. CONTINGENCY TABLES AND RELATED STATISTICS FROM LINEAR REGRESSION, FOR BOTH DEPENDENT (3682 OBSERVATIONS) AND INDEPENDENT (1841 OBSERVATIONS) NORTH PACIFIC OCEAN, JULY 1979, DATA

DEPENDENT DATA

FORECAST	OBSERVED 1	OBSERVED 2	OBSERVED 3
3	389	342	2131
2	0	0	0
1	427	156	237

AO = .69 AAO = .14

A1 = .14

TS1 = .35 ATS1 = .17

TS2 = 0.0 ATS2 = -.16

TS12 = .28 ATS12 = -.13

INDEPENDENT DATA

FORECAST	OBSERVED 1	OBSERVED 2	OBSERVED 3
3	189	176	1076
2	0	0	0
1	199	70	131

AO = .69 AAO = .11

A1 = .13

TS1 = .34 ATS1 = .16

TS2 = 0.0 ATS2 = -.15

TS12 = .26 ATS12 = -.13

TABLE IX. THE INITIAL FIVE BEST PREDICTORS FOR EPI'S OF FOUR THROUGH TEN, FOR EACH STRATEGY, WITH ASSOCIATED PP, a_0, a_1 AND CE VALUES FROM THE NORTH ATLANTIC OCEAN AREA 3W DEPENDENT DATA, 15 MAY-15 JULY 1983, WITHOUT LINEAR-REGRESSION EQUATIONS AS PREDICTORS

		Maximum-probability				Natural-regression		
EPI	Predictor	PP	a_0	a_1	CE	a_0	a_1	CE
4	E850	.372	.697	.125	.482	.514	.446	.526
	SHF	.376	.691	.125	.493	.512	.455	.521
	DTDP	.344	.685	.125	.505	.611	.304	.474
	E925	.359	.685	.125	.505	.505	.453	.537
	SMF	.334	.682	.125	.511	.606	.301	.487
5	E925	.367	.702	.125	.472	.564	.379	.494
	E850	.375	.700	.125	.475	.576	.370	.478
	DTDP	.344	.699	.125	.477	.528	.409	.535
	SHF	.379	.698	.125	.479	.567	.383	.483
	SMF	.337	.686	.125	.503	.526	.409	.539
6	DTDP	.353	.710	.125	.456	.568	.360	.503
	E850	.374	.699	.125	.477	.609	.324	.458
	SMF	.341	.699	.125	.477	.563	.360	.514
	E925	.363	.695	.125	.485	.595	.334	.476
	SHF	.374	.693	.125	.489	.512	.455	.521
7	DTDP	.356	.716	.125	.443	.514	.429	.542
	SMF	.348	.706	.125	.463	.590	.325	.495
	E850	.379	.699	.125	.477	.561	.389	.489
	E925	.364	.692	.125	.491	.547	.400	.506
	SHF	.376	.691	.125	.493	.548	.407	.497
8	SMF	.352	.714	.125	.448	.543	.386	.528
	DTDP	.356	.712	.125	.451	.611	.304	.474
	E850	.378	.700	.125	.475	.588	.355	.469
	SHF	.379	.691	.125	.493	.512	.455	.521
	E925	.364	.685	.125	.505	.577	.360	.486

TABLE IX (CONT.)

9	SMF	.352	.714	.125	.448	.563	.360	.514
	DTDP	.351	.708	.125	.459	.568	.360	.504
	SHF	.382	.700	.125	.475	.541	.417	.501
	E850	.376	.699	.125	.477	.550	.402	.498
	E925	.369	.699	.125	.477	.537	.414	.512
10	SMF	.357	.719	.125	.437	.526	.409	.539
	DTDP	.354	.710	.125	.455	.581	.341	.497
	E925	.369	.702	.125	.471	.564	.379	.493
	E850	.380	.700	.125	.475	.576	.370	.478
	SHF	.381	.698	.125	.479	.567	.383	.483

TABLE X. FIRST-STAGE CONTINGENCY TABLE STATISTICS A0, TS1, AA0 AND ATS1 FOR BOTH DEPENDENT AND INDEPENDENT NORTH ATLANTIC OCEAN AREA 3W, 15 MAY-15 JULY 1983, DATA, FOR EPI'S OF FOUR THROUGH TEN AND THE MAXIMUM-PROBABILITY STRATEGY, WITHOUT LINEAR-REGRESSION EQUATIONS AS PREDICTORS

		Dependent				Independent			
EPI	Best Predictor	A0	TS1	AA0	ATS1	A0	TS1	AA0	ATS1
4	E850	.70	.32	.05	.15	.69	.30	-.01	.14
5	E925	.70	.30	.06	.13	.71	.30	.05	.14
6	DTDP	.71	.32	.09	.15	.71	.29	.05	.13
7	DTDP	.72	.31	.11	.14	.71	.28	.07	.11
8	SMF	.71	.28	.10	.10	.73	.29	.13	.13
9	SMF	.71	.26	.10	.08	.73	.26	.11	.09
10	SMF	.71	.26	.09	.08	.73	.24	.15	.06

TABLE XI. SAME AS TABLE IX, EXCEPT WITH LINEAR-REGRESSION EQUATIONS AS PREDICTORS

			Maximum-probability			Natural-regression		
EPI	Predictor	PP	a_0	a_1	CE	a_0	a_1	CE
4	BM1	.443	.753	.125	.370	.662	.282	.394
	BM3	.427	.742	.125	.392	.665	.270	.400
	BM2	.395	.713	.125	.450	.516	.455	.512
	BM7	.389	.705	.125	.465	.512	.461	.515
	E850	.372	.697	.125	.482	.514	.446	.526
5	BM1	.438	.749	.125	.377	.589	.380	.442
	BM3	.433	.749	.125	.377	.590	.374	.446
	BM2	.400	.727	.125	.421	.566	.387	.482
	BM7	.396	.716	.125	.444	.564	.393	.480
	E925	.367	.702	.125	.472	.564	.379	.494
6	BM1	.449	.752	.125	.372	.628	.332	.413
	BM3	.433	.746	.125	.383	.625	.328	.422
	BM7	.404	.725	.125	.425	.604	.338	.453
	BM2	.399	.723	.125	.429	.517	.454	.512
	DTDP	.353	.710	.125	.456	.568	.360	.503
7	BM1	.452	.745	.125	.385	.650	.303	.397
	BM3	.434	.740	.125	.394	.575	.393	.457
	BM2	.406	.728	.125	.419	.554	.406	.486
	BM7	.404	.721	.125	.434	.480	.505	.536
	DTDP	.356	.716	.125	.443	.514	.429	.542
8	BM1	.453	.753	.125	.370	.606	.358	.431
	BM3	.441	.742	.125	.392	.601	.358	.440
	BM2	.405	.724	.125	.427	.585	.364	.466
	BM7	.406	.723	.125	.429	.575	.378	.472
	SMF	.352	.714	.125	.448	.543	.386	.528

TABLE XI (CONT.)

9	BM1	.453	.752	.125	.372	.689	.250	.372
	BM3	.442	.744	.125	.387	.685	.248	.381
	BM7	.410	.723	.125	.430	.540	.427	.493
	BM2	.405	.721	.125	.434	.547	.414	.491
	SMF	.352	.714	.125	.448	.563	.360	.514
10	BM1	.456	.749	.125	.377	.704	.235	.356
	BM3	.444	.749	.125	.377	.647	.301	.404
	BM2	.411	.727	.125	.421	.576	.377	.471
	BM7	.407	.721	.125	.433	.564	.393	.480
	SMF	.357	.719	.125	.438	.526	.409	.539

TABLE XII. SAME AS TABLE X, EXCEPT WITH LINEAR-REGRESSION EQUATIONS AS PREDICTORS AND BM1 IS THE PREDICTOR FOR EACH NUMBER OF EPI'S

	Dependent				Independent			
EPI	A0	TS1	AA0	ATS1	A0	TS1	AA0	ATS1
4	.75	.45	.22	.32	.74	.43	.17	.30
5	.75	.42	.21	.28	.75	.41	.17	.28
6	.75	.41	.22	.27	.75	.40	.18	.26
7	.75	.37	.20	.22	.75	.39	.19	.25
8	.75	.45	.22	.32	.74	.43	.17	.30
9	.75	.44	.22	.31	.75	.42	.18	.29
10	.75	.42	.21	.28	.75	.41	.17	.28

TABLE XIII. FD(96), FD, RSS FD, a_0, $a_0(96)$, a_1 AND $a_1(05)$ FOR STRATEGY MAXPROB2, NORTH ATLANTIC OCEAN AREA 3W, 15 MAY-15 JULY 1983, DEPENDENT DATA, WITHOUT LINEAR-REGRESSION EQUATIONS AS PREDICTORS, FOR THOSE PREDICTORS SELECTED AT EACH STAGE OF THE DEVELOPMENTAL MODEL USING EIGHT EPI'S. FD(96) IS COMPUTED FROM 100 RANDOMLY GENERATED DATA SETS, AS EXPLAINED IN APPENDIX A, AND PROVIDES A MEASURE OF HOW MUCH ADDITIONAL PREDICTABILITY MAY BE EXPECTED FROM THE INCLUSION OF A NEW PREDICTOR. IDEALLY, RSS FD SHOULD BE LESS THAN FD(96). STATISTICS $a_0(96)$ AND $a_1(05)$ ARE CRITICAL LEVEL STATISTICS FOR DETERMINING THE SIGNIFICANCE OF RESULTS. FOR RESULTS TO BE SIGNIFICANTLY BETTER THAN CHANCE, a_0 SHOULD BE GREATER THAN OR EQUAL TO $a_0(96)$ AND a_1 SHOULD BE LESS THAN OR EQUAL TO $a_1(05)$

Predictor Added	FD(96)	FD, of predictor added, on SMF	D850	RH	UBLW	RSS FD	a_0	$a_0(96)$	a_1	$a_1(05)$
SMF	-	-	-	-	-	-	.714	.386	.125	.341
D850	.1127	.1022	-	-	-	.1022	.724	.444	.125	.347
RH	.1594	.1026	.1014	-	-	.1443	.792	.603	.107	.246
UBLW	.1952	.1247	.1071	.1111	-	.1984	.927	.729	.037	.173
ENTRN	.2254	.1414	.1283	.1226	.1085	.2515	.983	*	.011	*

*Critical level statistics $a_0(96)$ and $a_1(05)$ could not be computed due to a 60 minute limit of central processing unit (CPU) time imposed by the NPS W.R. Church Computer Center.

TABLE XIV. FD(96), FD, RSS FD AND a_0 FOR STRATEGY MAXPROB2, NORTH ATLANTIC OCEAN AREA 3W, 15 MAY-15 JULY 1983, DEPENDENT DATA, WITHOUT LINEAR-REGRESSION EQUATIONS AS PREDICTORS, FOR THOSE PREDICTORS SELECTED AT EACH STAGE OF THE DEVELOPMENTAL MODEL USING FIVE EPI'S. FD(96) IS COMPUTED FROM 100 RANDOMLY GENERATED DATA SETS, AS EXPLAINED IN APPENDIX A, AND PROVIDES A MEASURE OF HOW MUCH ADDITIONAL PREDICTABILITY MAY BE EXPECTED FROM THE INCLUSION OF A NEW PREDICTOR. IDEALLY, RSS FD SHOULD BE LESS THAN FD(96).

		FD, of predictor added, on						
Predictor Added	FD(96)	E925	U700	DVDP	STRTFQ	ENTRN	RSS FD	a_0
E925	-	-	-	-	-	-	-	.702
U700	.1518	.1510	-	-	-	-	.1510	.706
DVDP	.2147	.1581	.1494	-	-	-	.2175	.733
STRTFQ	.2629	.1557	.1904	.1427	-	-	.2844	.813
ENTRN	.3036	.1665	.1556	.1734	.1387	-	.3178	.918
PS	.3394	.1897	.1779	.1492	.1971	.1495	.3887	.950

TABLE XV. SAME AS TABLE XIII, EXCEPT WITH LINEAR-REGRESSION EQUATIONS AS PREDICTORS AND FOR FOUR EPI'S

Predictor Added	FD(96)	FD, of predictor added, on					RSS FD	a_0	$a_0(96)$	a_1	$a_1(05)$
		BM1	U850	D500	V850	D1000					
BM1	-	-	-	-	-	-	-	.753	.376	.125	.313
U850	.1976	.2232	-	-	-	-	.2232	.755	.398	.125	.351
D500	.2794	.2242	.1813	-	-	-	.2883	.766	.444	.125	.341
U850	.3422	.2748	.2436	.2229	-	-	.4296	.789	.524	.118	.299
D1000	.3952	.2806	.2092	.3165	.2020	-	.5134	.834	.605	.100	.247
U1000	.4418	.2607	.4522	.2275	.1911	.2051	.6347	.891	.661	.068	.213

TABLE XVI. SAME AS TABLE XV, EXCEPT FOR EIGHT EPI'S

Predictor Added	FD(96)	FD, of predictor added, on: BM1	U500	ENTRN	DVDP	RSS FD	a_0	$a_0(96)$	a_1	$a_1(05)$
BM1	-	-	-	-	-	-	.753	.380	.125	.337
U500	.1127	.0899	-	-	-	.0899	.755	.443	.125	.345
ENTRN	.1594	.1051	.1058	-	-	.1491	.809	.598	.108	.252
DVDP	.1952	.1020	.1146	.1023	-	.1844	.925	.731	.047	.171
BM4	.2254	.1319	.1238	.1109	.1153	.2415	.971	*	.018	*

*Critical level statistics $a_0(96)$ and $a_1(05)$ could not be computed due to a 60 minute limit of central processing unit (CPU) time imposed by the NPS W.R. Church Computer Center.

TABLE XVII. CONTINGENCY TABLES AND RELATED STATISTICS FOR BOTH DEPENDENT (1526 OBSERVATIONS) AND INDEPENDENT (762 OBSERVATIONS) NORTH ATLANTIC OCEAN AREA 3W, 15 MAY-15 JULY 1983, DATA, WITHOUT LINEAR-REGRESSION EQUATIONS AS PREDICTORS, FROM STAGE FIVE OF THE DEVELOPMENTAL MODEL. PREDICTORS ARE SMF, D850, RH, UBLW AND ENTRN, EACH DIVIDED INTO EIGHT EPI'S, FOR (a) MAXPROB1, (b) MAXPROB2 AND (c) NATURAL-REGRESSION

(a) MAXPROB1

DEPENDENT DATA

FORECAST	OBSERVED 1	2	3
3	8	11	1039
2	5	178	0
1	283	1	1

AO =	.98	AAO =	.95
A1 =	.01		
TS1 =	.95	ATS1 =	.94
TS2 =	.91	ATS2 =	.90
TS12 =	.95	ATS12 =	.92

INDEPENDENT DATA

FORECAST	OBSERVED 1	2	3
3	68	61	452
2	9	21	38
1	64	12	37

AO =	.70	AAO =	.04
A1 =	.16		
TS1 =	.34	ATS1 =	.19
TS2 =	.15	ATS2 =	.03
TS12 =	.27	ATS12 =	-.05

TABLE XVII (CONT.)

(b) MAXPROB2

DEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	0	0	1021
2	0	183	10
1	296	7	9

AO = .98 AAO = .95

A1 = .01

TS1 = .95 ATS1 = .94

TS2 = .92 ATS2 = .90

TS12 = .95 ATS12 = 92

INDEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	54	52	408
2	14	23	57
1	73	19	62

AO = .66 AAO = -.10

A1 = .19

TS1 = .33 ATS1 = .18

TS2 = .14 ATS2 = .02

TS12 = .27 ATS12 = -.05

TABLE XVII (CONT.)

(c) Natural-Regression

DEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	0	10	1031
2	15	179	9
1	281	1	0

AO =	.98	AAO =	.93
A1 =	.02		
TS1 =	.95	ATS1 =	.93
TS2 =	.84	ATS2 =	.81
TS12 =	.93	ATS12 =	.90

INDEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	54	56	407
2	30	28	91
1	57	10	29

AO =	.65	AAO =	-.15
A1 =	.25		
TS1 =	.32	ATS1 =	.16
TS2 =	.13	ATS2 =	.01
TS12 =	.24	ATS12 =	-.10

TABLE XVIII. SAME AS TABLE XVII, EXCEPT FOR FIVE EPI'S. PREDICTORS ARE E925, U700, DVDP, STRTFQ AND ENTRN

(a) MAXPROB1

DEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	36	49	1027
2	21	135	4
1	239	6	9

AO = .92 AAO = .74

A1 = .05

TS1 = .77 ATS1 = .71

TS2 = .63 ATS2 = .57

TS12 = .75 ATS12 = .63

INDEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	54	60	460
2	19	20	27
1	68	14	40

AO = .72 AAO = .09

A1 = .16

TS1 = .35 ATS1 = .20

TS2 = .14 ATS2 = .02

TS12 = .29 ATS12 = -.02

TABLE XVIII (CONT.)

(b) MAXPROB2

DEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	11	12	970
2	2	148	36
1	283	30	34

AO = .92 AAO = .74

A1 = .05

TS1 = .79 ATS1 = .73

TS2 = .65 ATS2 = .60

TS12 = .78 ATS12 = .67

INDEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	43	49	426
2	12	21	44
1	86	24	57

AO = .70 AAO = .03

A1 = .17

TS1 = .39 ATS1 = .25

TS2 = .14 ATS2 = .02

TS12 = .32 ATS12 = .01

TABLE XVIII (CONT.)

(c) Natural-Regression

DEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	3	43	986
2	76	142	54
1	217	5	0

AO= .88 AAO= .63

A1= .12

TS1= .72 ATS1= .65

TS2= .44 ATS2= .36

TS12= .51 ATS12= .28

INDEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	41	52	424
2	39	31	75
1	61	11	28

AO= .68 AAO= -.05

A1= .23

TS1= .34 ATS1= .19

TS2= .15 ATS2= .03

TS12= .27 ATS12=-.05

TABLE XIX. CONTINGENCY TABLES AND RELATED STATISTICS FOR BOTH DEPENDENT (1526 OBSERVATIONS) AND INDEPENDENT (762 OBSERVATIONS) NORTH ATLANTIC OCEAN AREA 3W, 15 MAY-15 JULY 1983, DATA, WITH LINEAR-REGRESSION EQUATIONS AS PREDICTORS, FROM STAGE FOUR OF THE DEVELOPMENTAL MODEL. PREDICTORS ARE BM1, U850, D500 AND V850, EACH DIVIDED INTO FOUR EPI'S, FOR (a) MAXPROB1, (b) MAXPROB2 AND (c) NATURAL-REGRESSION

(a) MAXPROB1

DEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	97	120	990
2	6	21	5
1	193	49	45

AO = .79   AAO = .34

A1 = .12

TS1 = .50   ATS1 = .37

TS2 = .10   ATS2 = -.02

TS12 = .40   ATS12 = .12

INDEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	45	74	499
2	4	5	4
1	92	15	24

AO = .78   AAO = .29

A1 = .13

TS1 = .51   ATS1 = .40

TS2 = .05   ATS2 = -.09

TS12 = .37   ATS12 = .09

TABLE XIX (CONT.)

(b) MAXPROB2

DEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	77	109	967
2	3	21	9
1	216	60	64

AO= .79	AAO= .34
A1= .12	
TS1= .51	ATS1= .40
TS2= .10	ATS2=-.02
TS12= .42	ATS12= .16

INDEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	36	68	481
2	3	8	6
1	102	18	40

AO= .78	AAO= .27
A1= .12	
TS1= .51	ATS1= .40
TS2= .08	ATS2= -.05
TS12= .39	ATS12= .12

(c) Natural-Regression

DEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	35	82	875
2	131	87	147
1	130	21	18

AO = .72 AAO = .11

A1 = .25

TS1 = .39 ATS1 = .24

TS2 = .19 ATS2 = .07

TS12 = .33 ATS12 = .02

INDEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	24	49	427
2	53	38	87
1	64	7	13

AO = .69 AAO = .01

A1 = .26

TS1 = .40 ATS1 = .26

TS2 = .16 ATS2 = .05

TS12 = .30 ATS12 = -.01

TABLE XX. SAME AS TABLE XIX, EXCEPT RESULTS ARE FROM STAGE TWO IN THE DEVELOPMENTAL MODEL AND PREDICTORS ARE DIVIDED INTO EIGHT EPI'S EACH. PREDICTORS ARE BM1 AND U500

(a) MAXPROB1

DEPENDENT DATA

FORECAST	OBSERVED 1	OBSERVED 2	OBSERVED 3
3	112	130	965
2	10	13	9
1	174	47	66

AO =	.75	AAO =	.23
A1 =	.13		
TS1 =	.43	ATS1 =	.29
TS2 =	.06	ATS2 =	-.07
TS12 =	.33	ATS12 =	.02

INDEPENDENT DATA

FORECAST	OBSERVED 1	OBSERVED 2	OBSERVED 3
3	56	79	484
2	1	0	3
1	84	15	40

AO =	.75	AAO =	.17
A1 =	.13		
TS1 =	.43	ATS1 =	.30
TS2 =	0.0	ATS2 =	-.14
TS12 =	.30	ATS12 =	-.01

TABLE XX (CONT.)

(b) MAXPROB2

DEPENDENT DATA

FORECAST	1 (OBSERVED)	2 (OBSERVED)	3 (OBSERVED)
3	90	118	943
2	3	6	4
1	203	66	93

AO = .75 AAO = .23

A1 = .13

TS1 = .45 ATS1 = .31

TS2 = .03 ATS2 = -.11

TS12 = .36 ATS12 = .06

INDEPENDENT DATA

FORECAST	1 (OBSERVED)	2 (OBSERVED)	3 (OBSERVED)
3	46	76	470
2	0	0	2
1	95	18	55

AO = .74 AAO = .16

A1 = .13

TS1 = .44 ATS1 = .32

TS2 = 0.0 ATS2 = -.14

TS12 = .33 ATS12 = .02

TABLE XX (CONT.)

(c) Natural-Regression

DEPENDENT DATA

FORECAST	OBSERVED 1	OBSERVED 2	OBSERVED 3
3	59	97	873
2	170	76	156
1	67	17	11

AO = .67 AAO = -.05

A1 = .29

TS1 = .21 ATS1 = .02

TS2 = .15 ATS2 = .03

TS12 = .22 ATS12 = -.15

INDEPENDENT DATA

FORECAST	OBSERVED 1	OBSERVED 2	OBSERVED 3
3	32	64	431
2	74	25	90
1	35	5	6

AO = .64 AAO = -.15

A1 = .31

TS1 = .23 ATS1 = .06

TS2 = .10 ATS2 = -.03

TS12 = .18 ATS12 = -.18

TABLE XXI. LINEAR-REGRESSION EQUATIONS FOR THE PREDICTED VALUE OF THE VISIBILITY CATEGORY ($\hat{Y}$), FOR BOTH REGRESSION METHODS, $\hat{Y}$ STATISTICS WITH RESPECT TO THE ACTUAL VISIBILITY CATEGORIES (Y) AND THRESHOLD VALUES FROM BOTH THRESHOLD MODELS, NORTH ATLANTIC OCEAN AREA 3W, 15 MAY-15 JULY 1983. NOTATION IS AS IN APPENDIX B

A. Definitions:

LR1 - Linear regression method 1: single equation, three visibility categories

LR2 - Linear regression method 2: Decision-tree; two equations, two visibility categories each

a - All predictors were made available to the regression model.

b - Only the best predictors from the Preisendorfer (1983 a,b,c) methodology were made available to the regression model

A - Quadratic threshold model (Case III, Appendix B)

B - Equal variance threshold model (Case I, Appendix B)

B. LR1a

$$\hat{y} = 2.81132 + .16201(EAIR) - .00237(E850) - .07319(T925) - .16179(E925)$$

Class conditional distributions (i.e., the distribution of $\hat{y}$ for a given y).

y	Number of observations of y	Frequency of y (p)	Mean value of $\hat{y}$ (m)	Standard deviation of $\hat{y}$ (σ)
1	296	.194	2.014 (m_1)	.434
2	190	.125	2.324 (m_2)	.379
3	1040	.682	2.652 (m_3)	.352

LRlaA

T_1 = threshold between y = 1 and y = 2 = 2.275

T_2 = threshold between y = 2 and y = 3 = 1.839

T_3 = threshold between y = 1 and y = 3 = 2.008

(second threshold value, of the pair, was of no interest. See Appendix B)

LRlaB

T_a = threshold between y = 1 and y = 2 = 2.368

T_b = threshold between y = 2 and y = 3 = 1.768

T_c = threshold between y = 1 and y = 3 = 2.060

State conditional distributions for visibility category I (y = 1), II (y = 2) and III (y = 3) depicting threshold values and means.

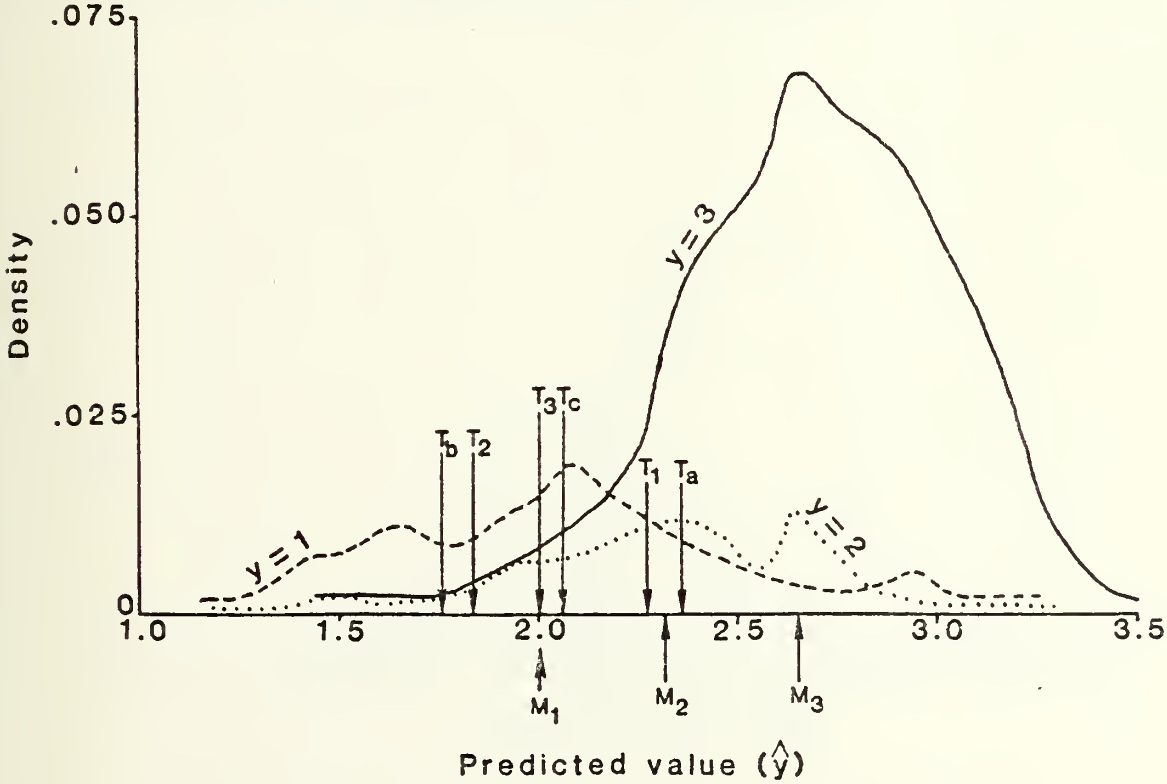


TABLE XXI (CONT.)

C. LR2a

Equation 1: $\hat{y} = .90305 + .06122(\text{EAIR}) + .11284 \times 10^{-4}(\text{D850}) - .08438(\text{E850}) - .04083(\text{T925})$

Class conditiona distributions

y	Number of observations of y	Frequency of y (p)	Mean value of $\hat{y}$ (m)	Standard Deviation of $\hat{y}$ (σ)
0	486	.318	.479 (m_0)	.222
1	1040	.682	.776 (m_1)	.209

LR2aA: T_1 = threshold between y = 0 and y = 1 = .4979

LR2aB: T_a = threshold between y = 0 and y = 1 = .5110

State conditional distributions for combined visibility categories I and II (y = 0) and visibility category III (y = 1) depicting threshold values and means

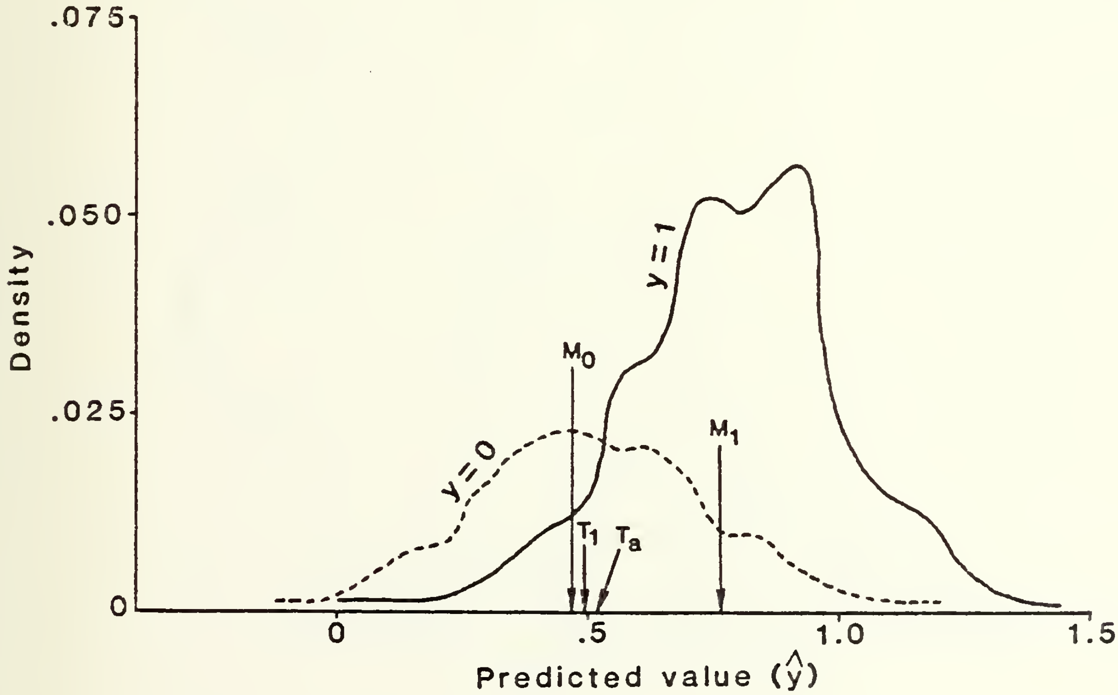


TABLE XXI (CONT.)

Equation 2:
$$\hat{y} = .01229 - .18917 \times 10^{-3}(U1000) - .02088(T500) + .1339 \times 10^{-3}(U500) + .15259 \times 10^{-4}(D925) - .32705 \times 10^{-2}(STRTFQ) + 7.50153(DEDP) - .03279(DVDP)$$

Class conditional distributions

y	Number of observations of y	Frequency of y (p)	Mean value of $\hat{y}$ (m)	Standard deviation of $\hat{y}$ (σ)
0	296	.609	.319 (m_0)	.186
1	190	.391	.503 (m_1)	.194

LR2aA: T_1 = threshold between y = 0 and y = 1 = .5102

LR2aB: T_a = threshold between y = 0 and y = 1 = .4972

State conditional distributions for visibility category I (y = 0) and II (y = 1) depicting threshold values and means.

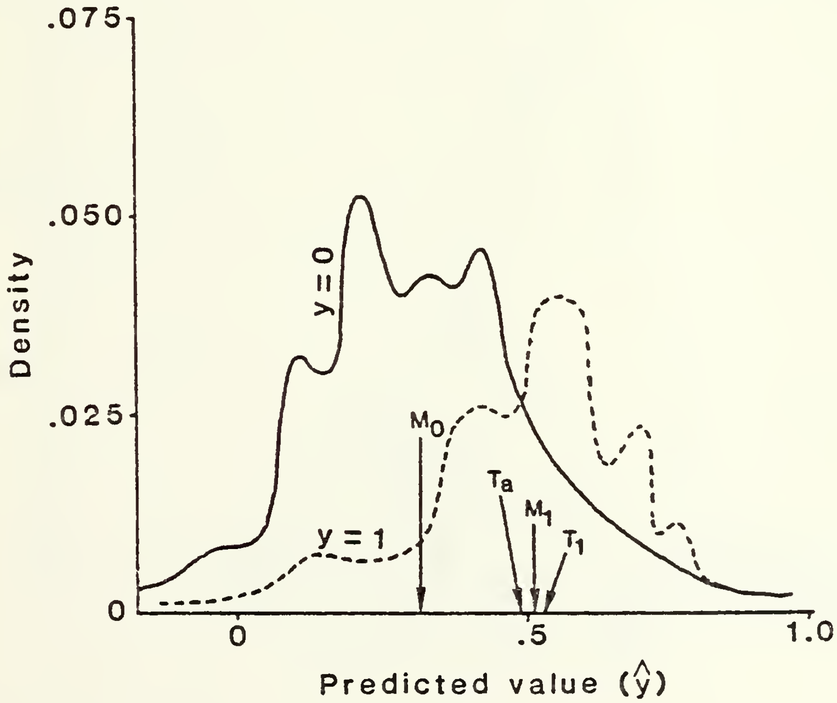


TABLE XXI (CONT.)

D. LR2b

Equation 1: $\hat{y} = .89952 - .04830(E850) + .02472(SHF) + 2.17081(DTDP) + 6.81684(DEDP)$

Class conditional distributions

y	Number of observations of y	Frequency of y (p)	Mean value of $\hat{y}$ (m)	Standard deviation of $\hat{y}$ (σ)
0	486	.318	.496 (m_0)	.220
1	1040	.682	.768 (m_1)	.201

LR2bA: T_1 = threshold between y = 0 and y = 1 = .4922

LR2bB: T_a = threshold between y = 0 and y = 1 = .5119

State conditional distributions for visibility categories I and II (y = 0) and visibility category III (y = 1) depicting threshold values and means.

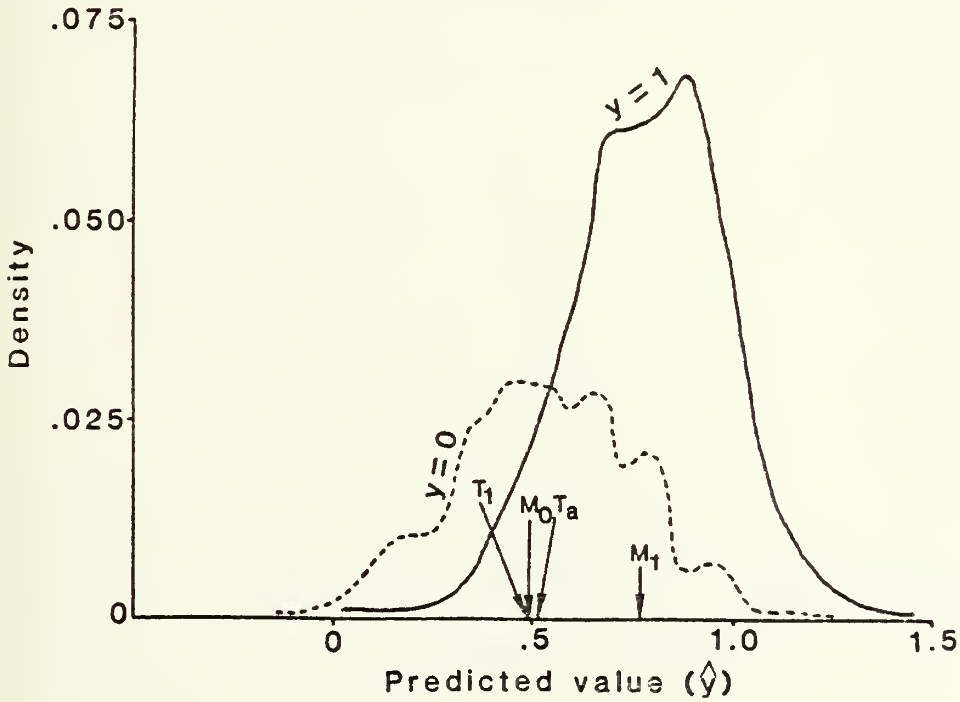


TABLE XXI (CONT.)

Equation 2: $\hat{y} = .71769 + .11439 \times 10^{-3}(V700) - .47810 \times 10^{-2}(STRTFQ) + 4.5433(DTDP)$

Class conditional distributions

y	Number of observations of y	Frequency of y (p)	Mean value of $\hat{y}$ (m)	Standard deviation of $\hat{y}$ (σ)
0	296	.609	.337 (m_0)	.164
1	190	.391	.476 (m_1)	.177

LR2bA: T_1 = threshold between y = 0 and y = 1 = .5208

LRabB: T_a = threshold between y = 0 and y = 1 = .4978

State conditional distributions for visibility category I (y = 0) and II (y = 1) depicting threshold values and means.

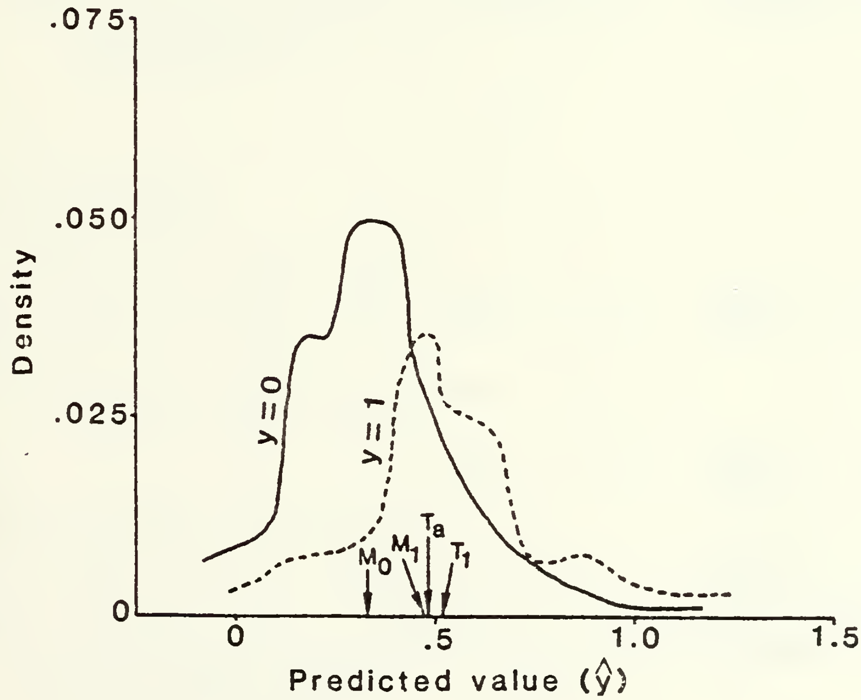


TABLE XXII. CONTINGENCY TABLES AND RELATED STATISTICS FROM LINEAR REGRESSION METHOD 1 (SINGLE EQUATION), QUADRATIC THRESHOLD MODEL, FOR BOTH DEPENDENT (1526 OBSERVATIONS) AND INDEPENDENT (762 OBSERVATIONS) NORTH ATLANTIC OCEAN AREA 3W, 15 MAY-15 JULY 1983, DATA, WITH ALL PREDICTORS AVAILABLE TO THE REGRESSION MODEL

LRlaA (Table XXI)

DEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	152	151	996
2	0	0	0
1	144	39	44

AO = .75 AAO = .21

A1 = .12

TS1 = .38 ATS1 = .23

TS2 = 0.0 ATS2 = -.14

TS12 = .27 ATS12 = -.07

INDEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	69	80	498
2	0	0	0
1	72	14	29

AO = .75 AAO = .18

A1 = .12

TS1 = .39 ATS1 = .25

TS2 = 0.0 ATS2 = -.14

TS12 = .27 ATS12 = -.05

TABLE XXIII. SAME AS TABLE XXII, EXCEPT USING THE EQUAL-VARIANCE THRESHOLD MODEL

LRlaB (Table XXI)

DEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	135	147	984
2	0	0	0
1	161	43	56

AO =	.75	AAO =	.22
A1 =	.12		
TS1 =	.41	ATS1 =	.27
TS2 =	0.0	ATS2 =	-.14
TS12 =	.30	ATS12 =	-.03

INDEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	65	78	492
2	0	0	0
1	76	16	35

AO =	.75	AAO =	.17
A1 =	.12		
TS1 =	.40	ATS1 =	.26
TS2 =	0.0	ATS2 =	-.14
TS12 =	.28	ATS12 =	-.04

TABLE XXIV. CONTINGENCY TABLES AND RELATED STATISTICS FROM LINEAR REGRESSION METHOD 2 (DECISION-TREE), QUADRATIC THRESHOLD MODEL, FOR BOTH DEPENDENT (1526 OBSERVATIONS) AND INDEPENDENT (762 OBSERVATIONS) NORTH ATLANTIC OCEAN AREA 3W, 15 MAY-15 JULY 1983, DATA, WITH ALL PREDICTORS AVAILABLE TO THE REGRESSION MODEL

LR2aA (Table XXI)

DEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	105	118	945
2	11	28	19
1	180	44	76

AO =	.76	AAO =	.23
A1 =	.13		
TS1 =	.43	ATS1 =	.30
TS2 =	.13	ATS2 =	.00
TS12 =	.36	ATS12 =	.06

INDEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	52	68	474
2	11	8	6
1	78	18	47

AO =	.73	AAO =	.14
A1 =	.14		
TS1 =	.38	ATS1 =	.24
TS2 =	.07	ATS2 =	-.06
TS12 =	.30	ATS12 =	-.01

TABLE XXV. SAME AS TABLE XXIV, EXCEPT USING THE EQUAL-VARIANCE THRESHOLD MODEL

LR2aB (Table XXI)

DEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	96	116	938
2	15	30	26
1	185	44	76

AO =	.76	AAO =	.23
A1 =	.13		
TS1 =	.44	ATS1 =	.31
TS2 =	.13	ATS2 =	.01
TS12 =	.37	ATS12 =	.07

INDEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	49	67	464
2	12	9	13
1	80	18	50

AO =	.73	AAO =	.11
A1 =	.14		
TS1 =	.38	ATS1 =	.24
TS2 =	.08	ATS2 =	-.05
TS12 =	.30	ATS12 =	-.01

TABLE XXVI. CONTINGENCY TABLES AND RELATED STATISTICS FROM LINEAR REGRESSION METHOD 2 (DECISION-TREE), QUADRATIC THRESHOLD MODEL, FOR BOTH DEPENDENT (1526 OBSERVATIONS) AND INDEPENDENT (762 OBSERVATIONS) NORTH ATLANTIC OCEAN AREA 3W, 15 MAY-15 JULY 1983, DATA, WITH ONLY THOSE PREDICTORS IDENTIFIED AS BEST BY THE PREISENDORFER METHODOLOGY AVAILABLE TO THE REGRESSION MODEL

LR2bA (Table XXI)

DEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	116	127	952
2	5	10	13
1	175	53	75

AO =	.75	AAO =	.20
A1 =	.13		
TS1 =	.41	ATS1 =	.27
TS2 =	.05	ATS2 =	-.09
TS12 =	.32	ATS12 =	.01

INDEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	54	72	475
2	4	1	7
1	83	21	45

AO =	.73	AAO =	.14
A1 =	.14		
TS1 =	.40	ATS1 =	.26
TS2 =	.01	ATS2 =	-.13
TS12 =	.29	ATS12 =	-.02

TABLE XXVII. SAME AS TABLE XXVI, EXCEPT USING THE EQUAL-VARIANCE THRESHOLD MODEL

LR2bB (Table XXI)

DEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	105	116	933
2	8	14	23
1	183	60	84

AO =	.74	AAO =	.19
A1 =	.14		
TS1 =	.42	ATS1 =	.28
TS2 =	.06	ATS2 =	-.07
TS12 =	.33	ATS12 =	.02

INDEPENDENT DATA

FORECAST \ OBSERVED	1	2	3
3	51	71	465
2	5	3	10
1	85	20	52

AO =	.73	AAO =	.11
A1 =	.14		
TS1 =	.40	ATS1 =	.26
TS2 =	.03	ATS2 =	-.11
TS12 =	.30	ATS12 =	-.02

TABLE XXVIII. SUMMARY OF THE CONTINGENCY TABLE STATISTICS FOR ALL MOS VARIATIONS USED IN THE NORTH ATLANTIC OCEAN AREA 3W, 15 MAY-15 JULY 1983

PM5 indicates results from the Preisendorfer (1983 a,b,c) methodology without linear regression equations as predictors and using five EPI's.

PM8 same as PM5, except using eight EPI's.

BPM4 indicates results from the Preisdendorfer (1983 a,b,c) methodology with linear regression equations as predictors and using four EPI's.

BPM8 same as BPM4, except using eight EPI's.

Linear regression notation is as in Table XXI.

		Dependent data						Independent data					
MOS method		A0	A1	AA0	ATS1	ATS2	ATS12	A0	A1	AA0	ATS1	ATS2	ATS12
PM5	MAXPROB1	.92	.05	.74	.71	.57	.63	.72	.16	.09	.20	.02	-.02
	MAXPROB2	.92	.05	.74	.73	.60	.67	.70	.17	.03	.25	.02	.01
	Nat. Reg.	.88	.12	.63	.65	.36	.28	.68	.23	-.05	.19	.03	-.05
PM8	MAXPROB1	.98	.01	.95	.94	.90	.92	.70	.16	.04	.19	.03	-.05
	MAXPROB2	.98	.01	.95	.94	.90	.92	.66	.19	-.10	.18	.02	-.05
	Nat. Reg.	.98	.02	.93	.93	.81	.90	.65	.25	-.15	.16	.01	-.10
BPM4	MAXPROB1	.79	.12	.34	.37	-.02	.12	.73	.13	.29	.40	-.09	.09
	MAXPROB2	.79	.12	.34	.40	-.02	.16	.78	.12	.27	.40	-.05	.12
	Nat. Reg.	.72	.25	.11	.24	.07	.02	.69	.26	.01	.26	.05	-.01
BPM8	MAXPROB1	.75	.13	.23	.29	-.07	.02	.75	.13	.17	.30	-.14	-.01
	MAXPROB2	.75	.13	.23	.31	-.11	.06	.74	.13	.16	.32	-.14	.02
	Nat. Reg.	.67	.29	-.05	.02	.03	-.15	.64	.31	-.15	.06	-.03	-.18
LR1aA		.75	.12	.21	.23	-.14	-.07	.75	.12	.18	.25	-.14	-.05
LR1aB		.75	.12	.22	.27	-.14	-.03	.75	.12	.17	.26	-.14	-.04
LR2aA		.76	.13	.23	.30	.00	.06	.73	.14	.14	.24	-.06	-.01
LR2aB		.76	.13	.23	.31	.01	.07	.73	.14	.11	.24	-.05	-.01
LR2bA		.75	.13	.20	.27	-.09	.01	.73	.14	.14	.26	-.13	-.02
LR2bB		.74	.14	.19	.28	-.07	.02	.73	.14	.11	.26	-.11	-.02

APPENDIX G

FIGURES

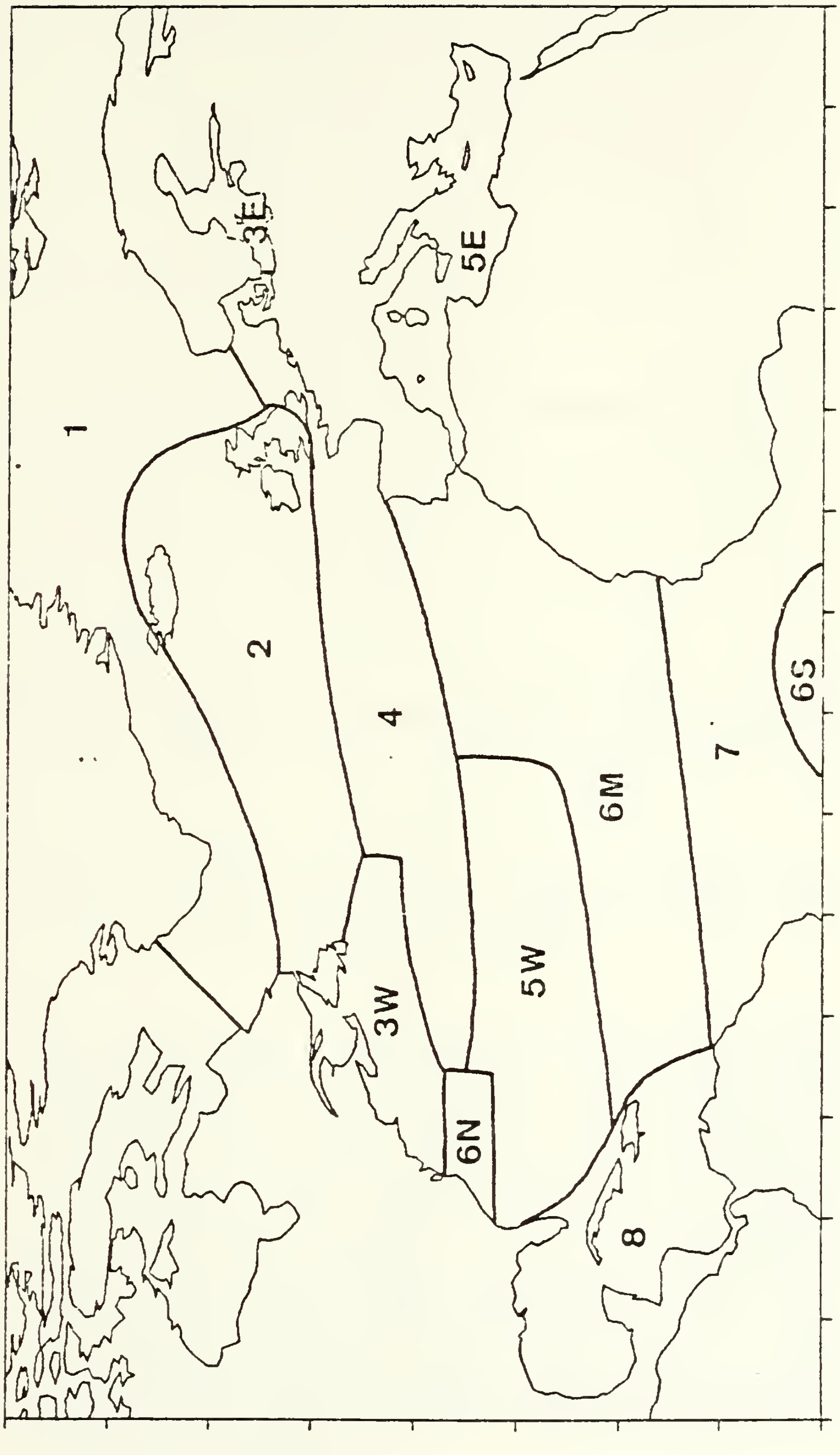


FIG. 1. Homogeneous Areas for the North Atlantic Ocean, June and July, from Lowe (1984b)

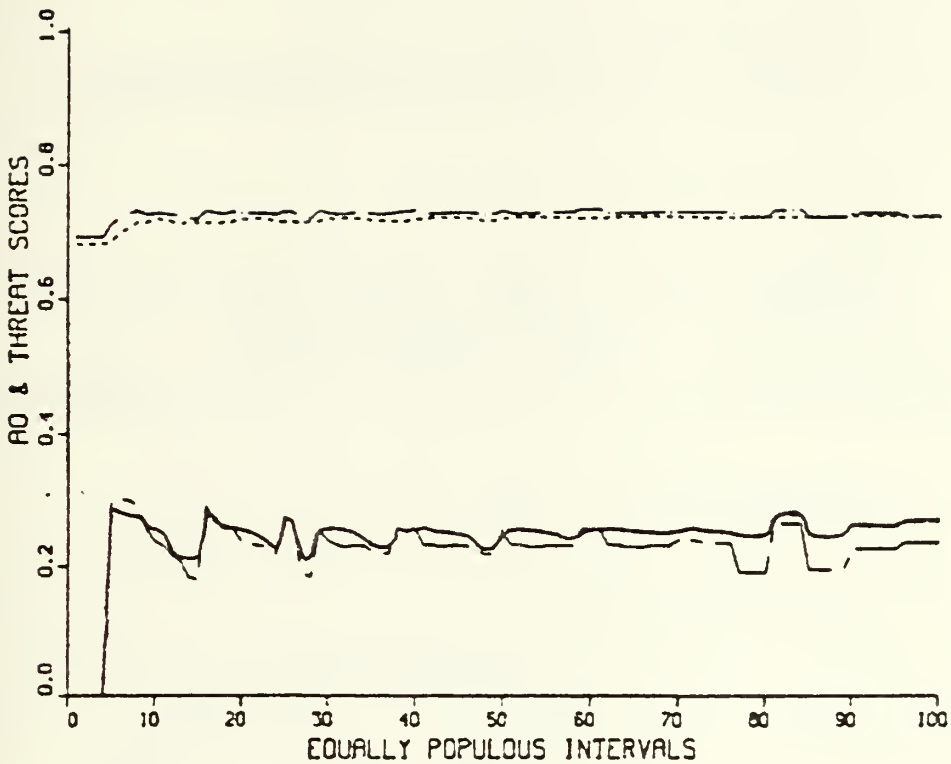


Fig. 2a. The behavior of contingency table statistics for dependent (A0--dashes, TS1--solid) and independent (A0--chaindots, TS1--chaindashes) data, as the number of EPI's is varied, for the North Atlantic Ocean area 3W, 15 May-15 July 1983, when predictors are chosen based upon the maximum increase of a_0 in the dependent data, for (a) a single predictor (SMF), (b) two predictors, (c) three predictors, (d) four predictors, and (e) five predictors. Numbers in parentheses represent the number of EPI's which was fixed for the indicated parameter so that the number of EPI's for the next predictor could be varied.

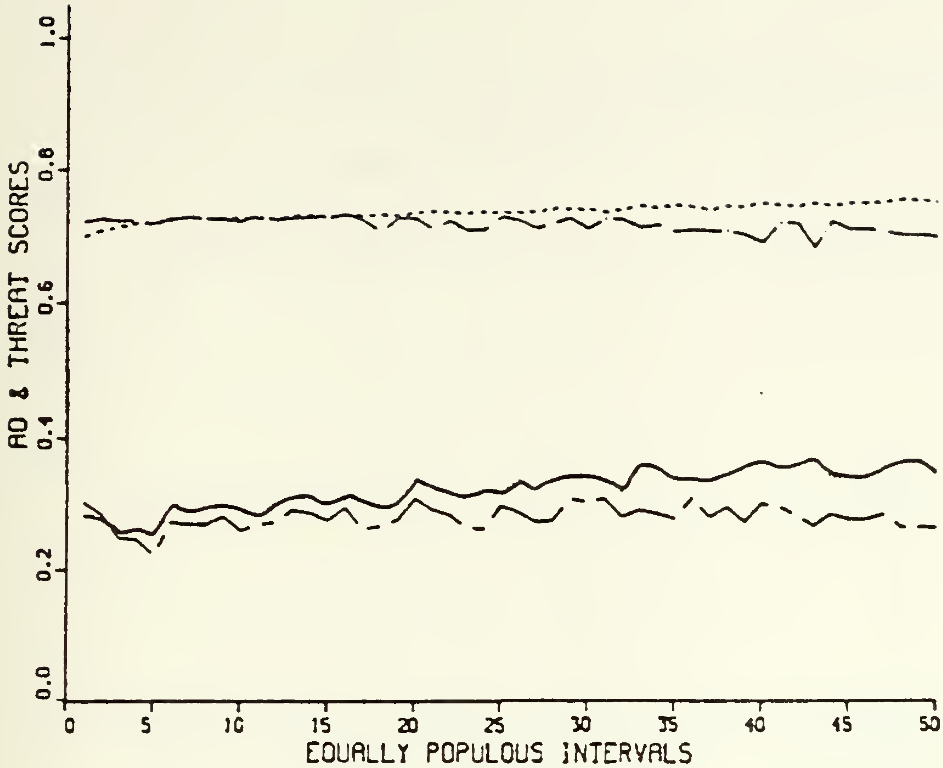


Fig. 2b. Same as Fig. 2a, except for two predictors (SMF(6) and DTDP).

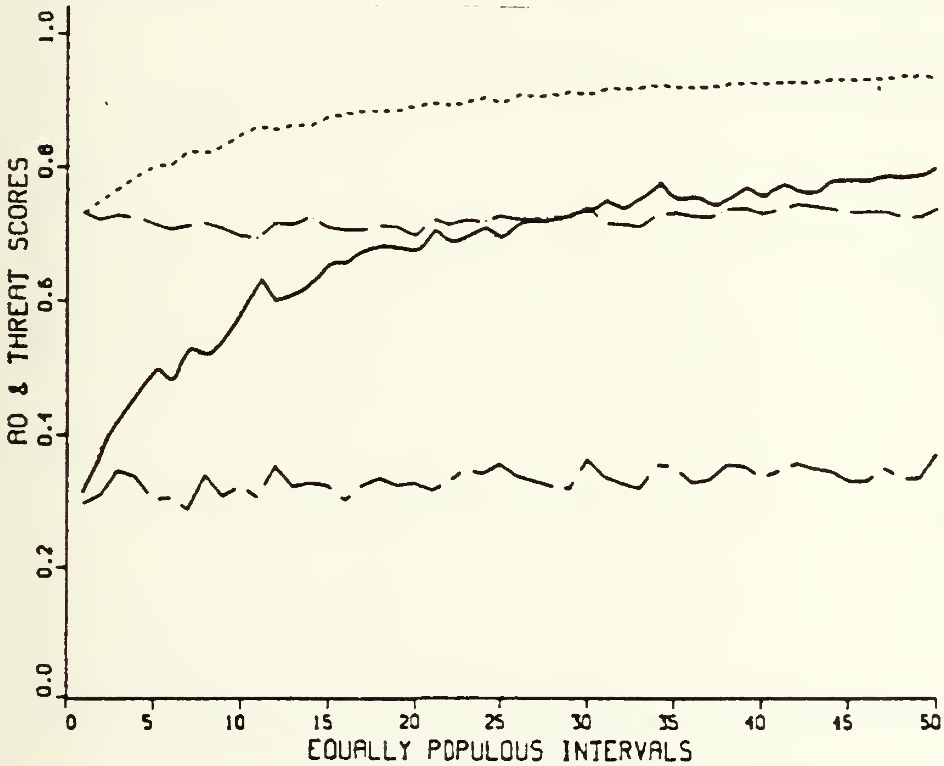


Fig. 2c. Same as Fig. 2a, except for three predictors (SMF(6), DTDP(16) and PS).

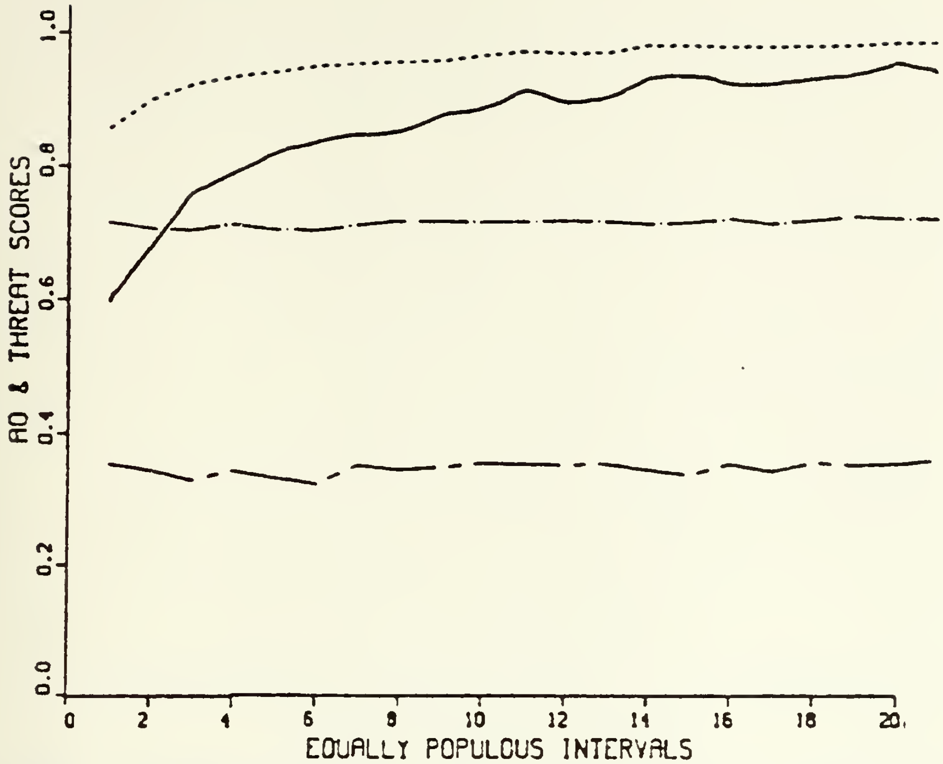


Fig. 2d. Same as Fig. 2a, except for four predictors (SMF(6), DTDP(16), PS(12) and UBLW).

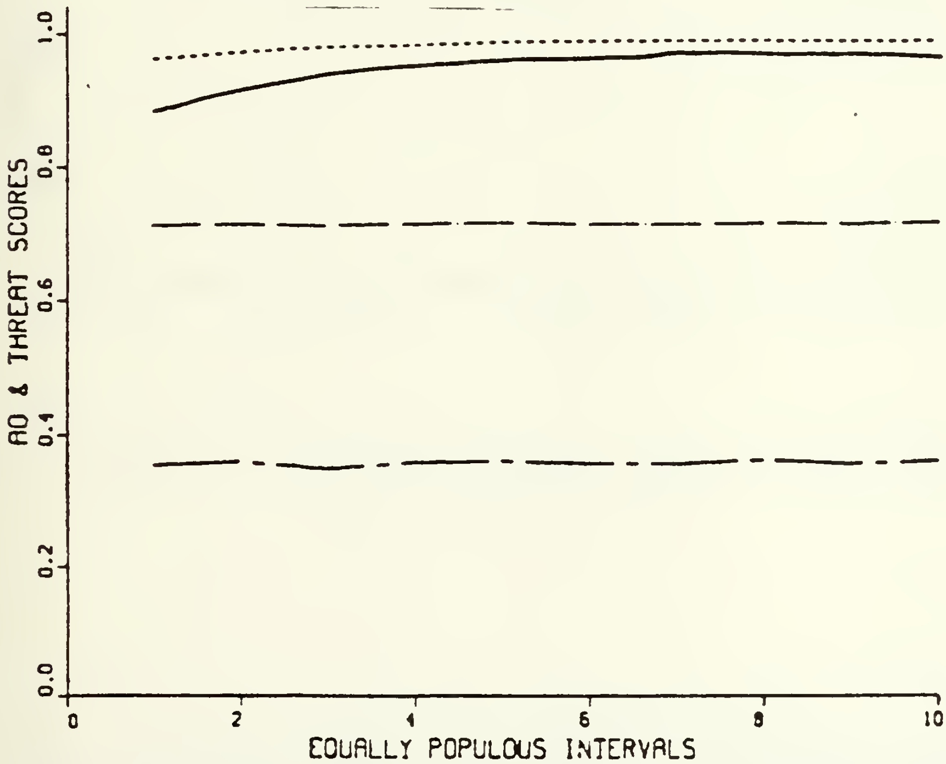


Fig. 2e. Same as Fig. 2a, except for five predictors (SMF(6), DTDP(16), PS(12), UBLW(10) and V400).

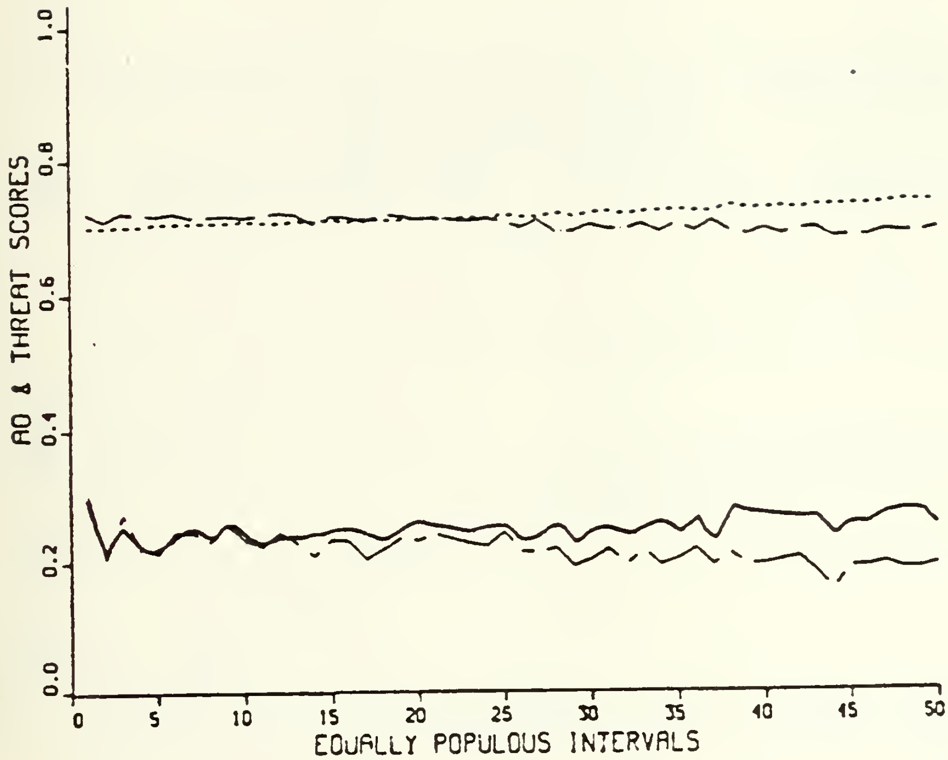


Fig. 3a. Same as Fig. 2a, except predictors, after the first, are selected by having the lowest RSS FD for (a) two predictors (SMF(6) and RH), (b) three predictors, (c) four predictors, (d) five predictors, and (e) six predictors.

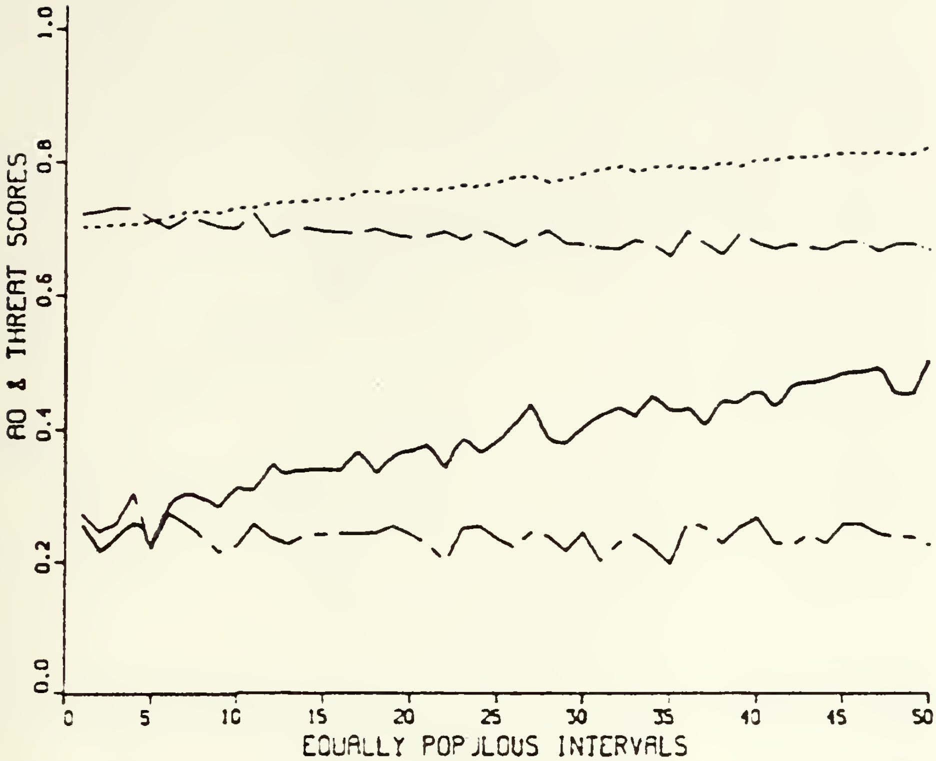


Fig. 3b. Same as Fig. 3a, except for three predictors (SMF(6), RH(3) and DUDP).

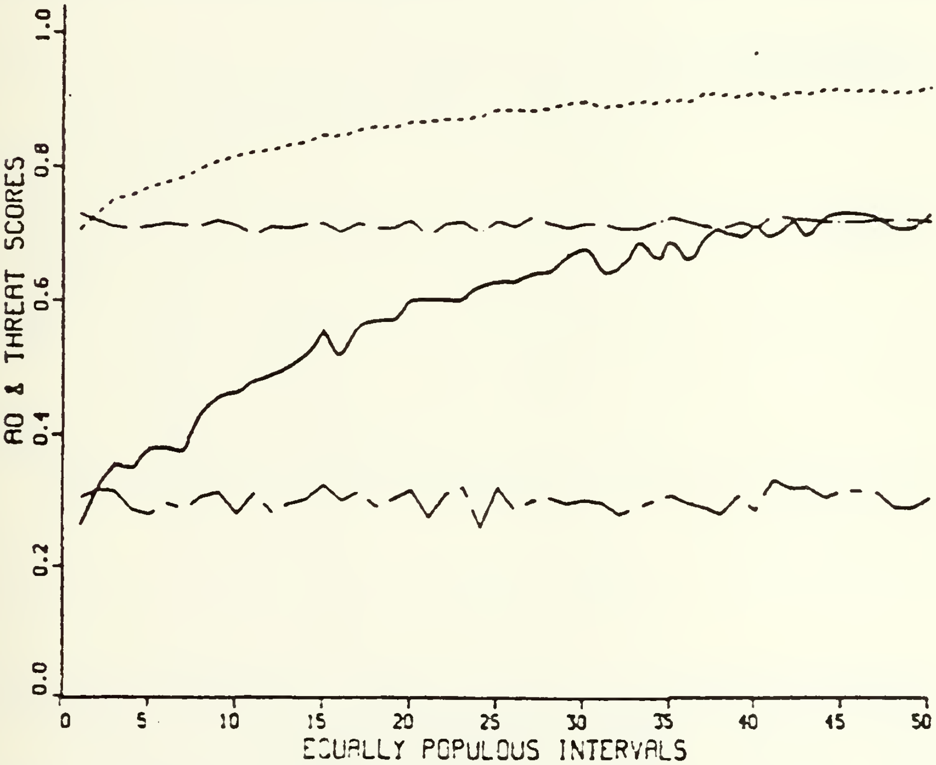


Fig. 3c. Same as Fig. 3a, except for four predictors (SMF(6), RH(3), DUDP(4) and VOP925).

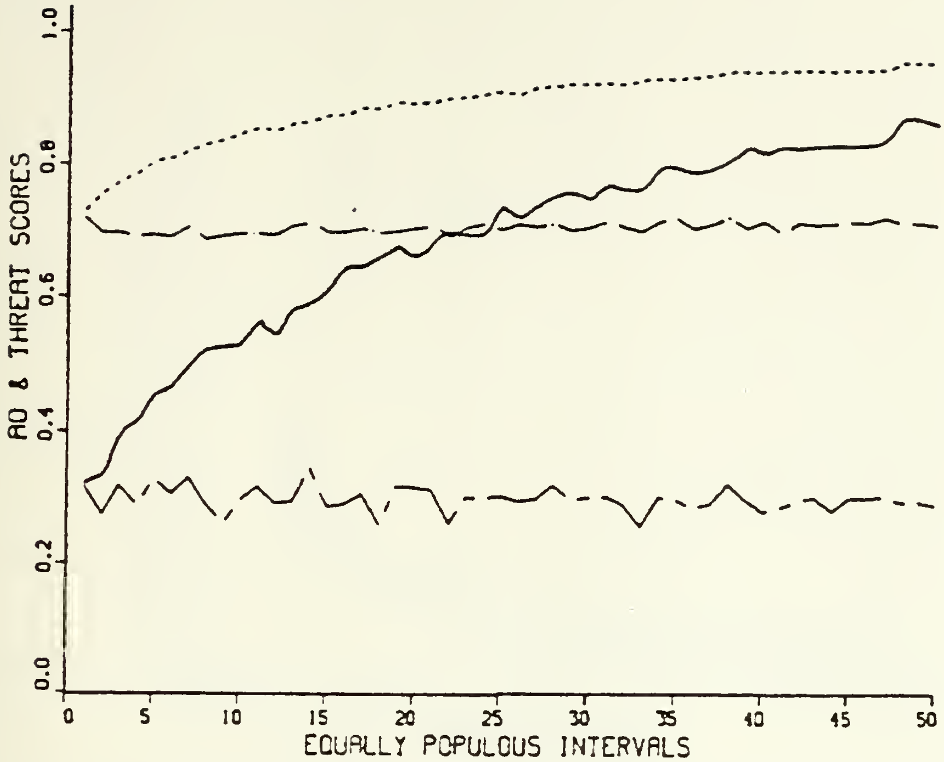


Fig. 3d. Same as Fig. 3a, except for five predictors (SMF(6), RH(3), DUDP(4), VOR925(2) and ENTRN).

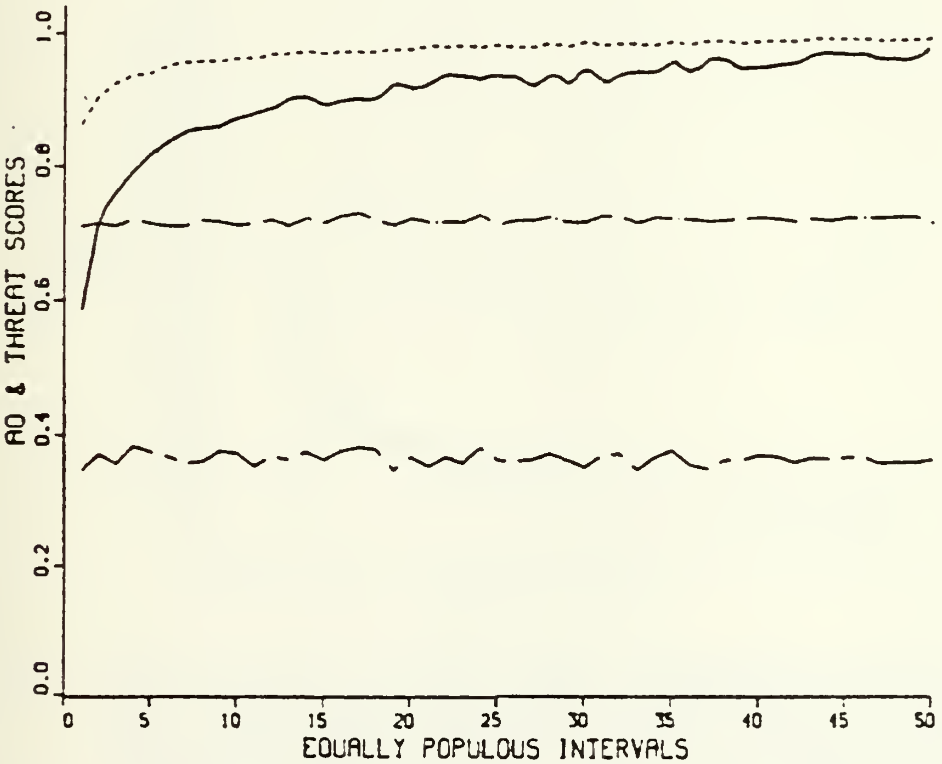


Fig. 3e. Same as Fig. 3a, except for six predictors (SMF(6), RH(3), DUDP(4), VOR925(2), ENTRN(14) and UBLW).

(a)

(b)

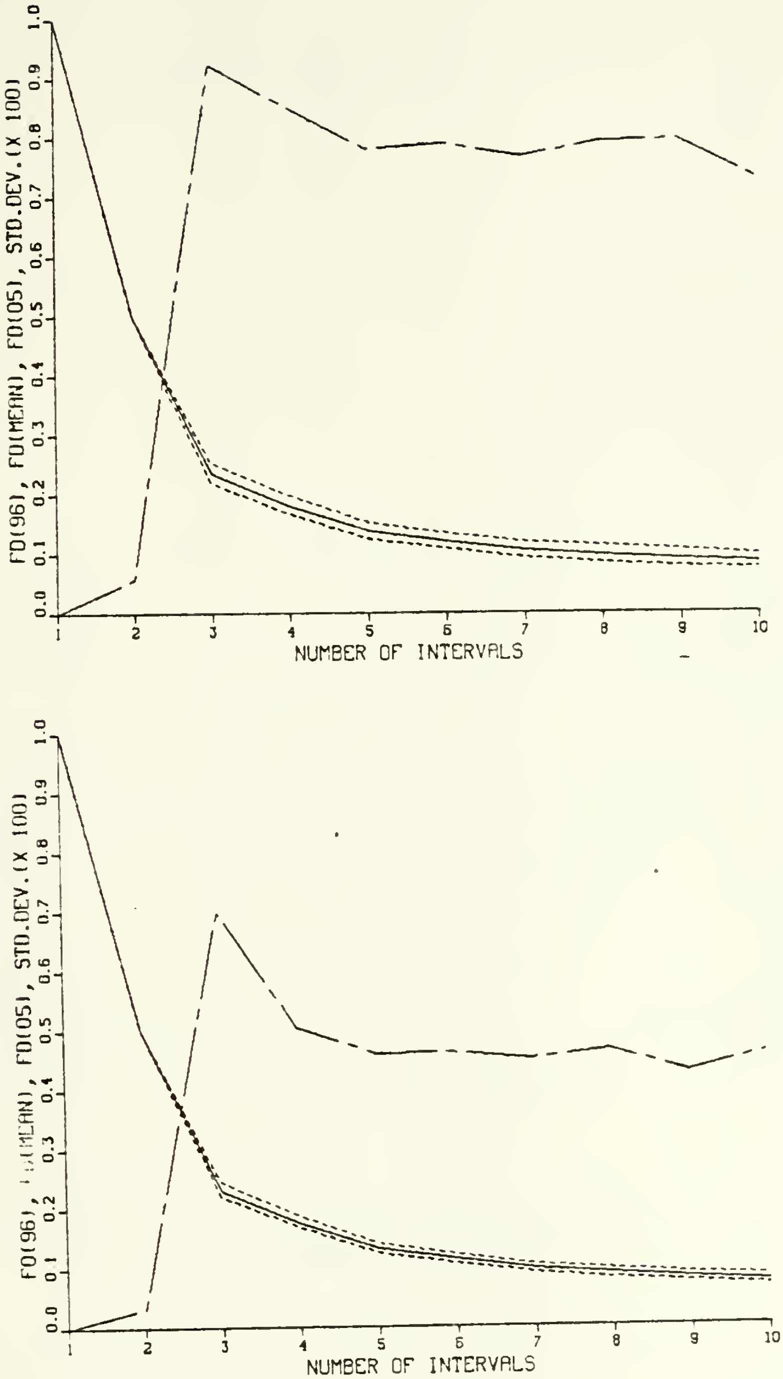


Fig. 4. The behavior of functional dependence (FD) as determined from 100 randomly generated data sets (Preisendorfer, 1983c) for EPI's of two through ten for (a) the North Atlantic Ocean area 3W, 15 May-15 July 1983, dependent data (1526 observations) and (b) the North Pacific Ocean, July 1979, dependent data (3682 observations). Plotted are FD(96) (upper dashed), FD(05), (lower dashed), mean FD (solid) and standard deviation (x 100) (chaindashes)

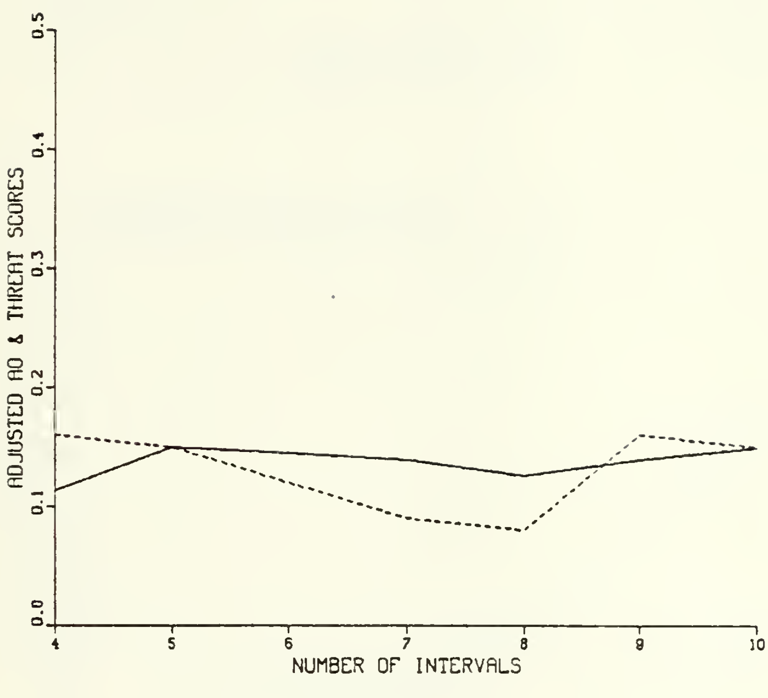
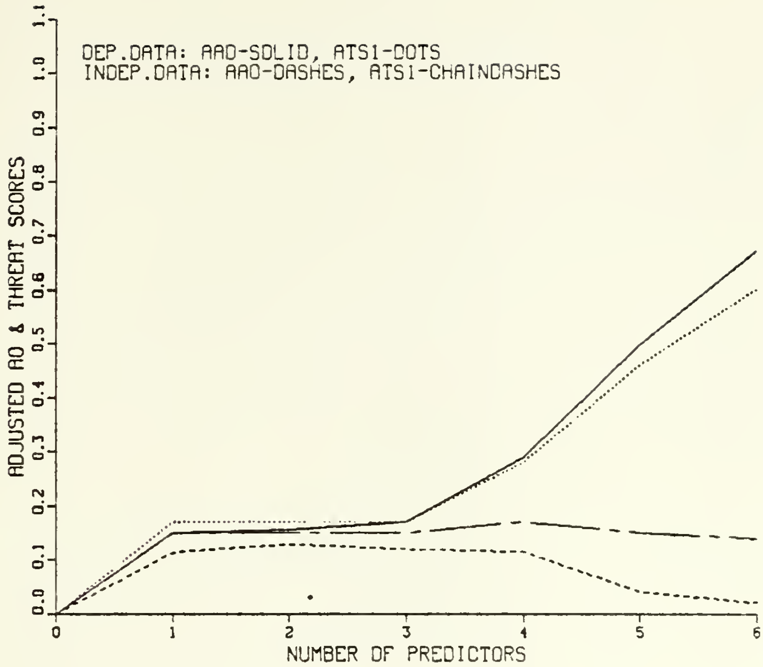


Fig. 5. First stage contingency table statistics AA0, dependent data (solid), and ATS1, independent data (dashed), North Pacific Ocean, July 1979, as a function of the number of EPI's, from the Preisendorfer (1983 a,b) methodology. EHF is the predictor for all EPI's.

(a)



(b)

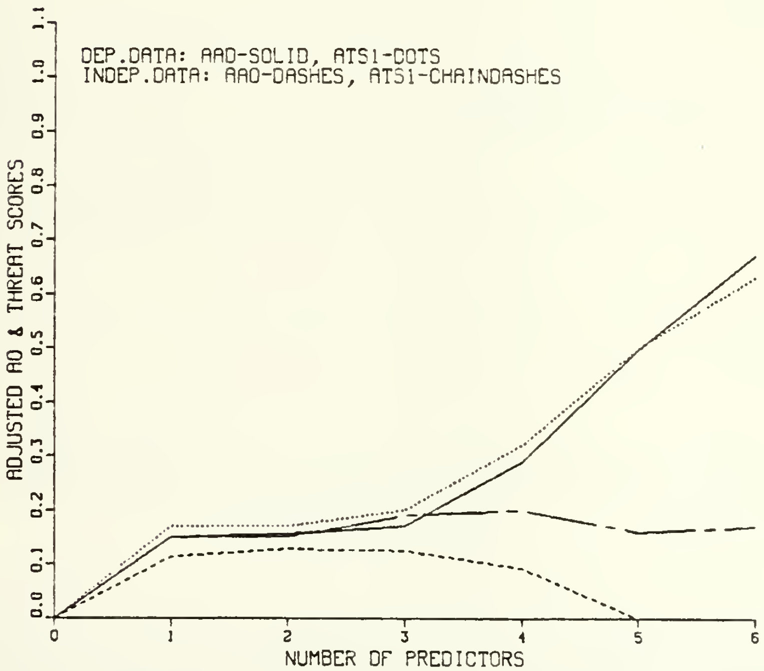


Fig. 6. Contingency table statistics AA0 and ATS1 for both dependent and independent North Pacific Ocean, July 1979, data as a function of the number of predictors in the model for strategies (a) MAXPROB1 and (b) MAXPROB2. Predictors are EHF, DDWW, H510, THF and CLIMO, each divided into five EPI's. Negative values are not plotted.

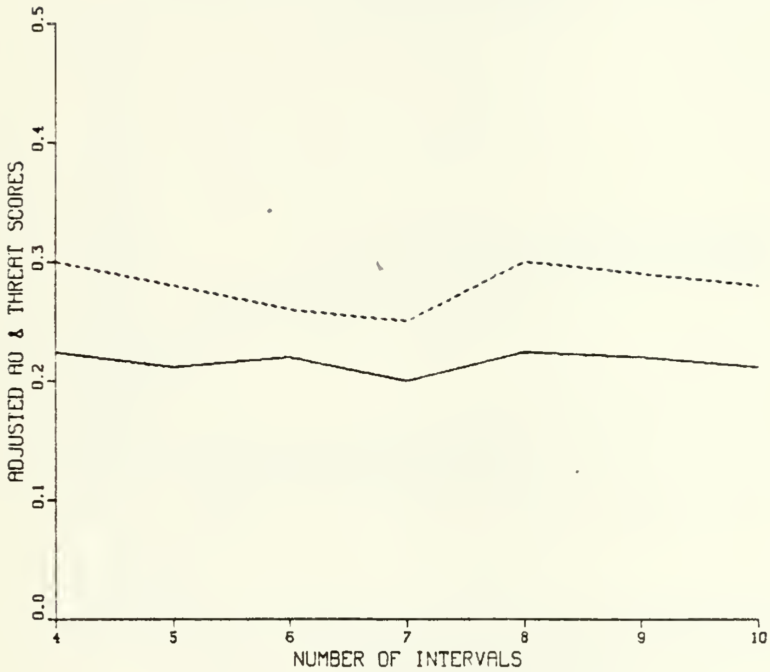


Fig. 7. Same as Fig. 5, except for the North Atlantic Ocean area 3W, 15 May-15 July 1983. BM1 is the predictor for all EPI's.

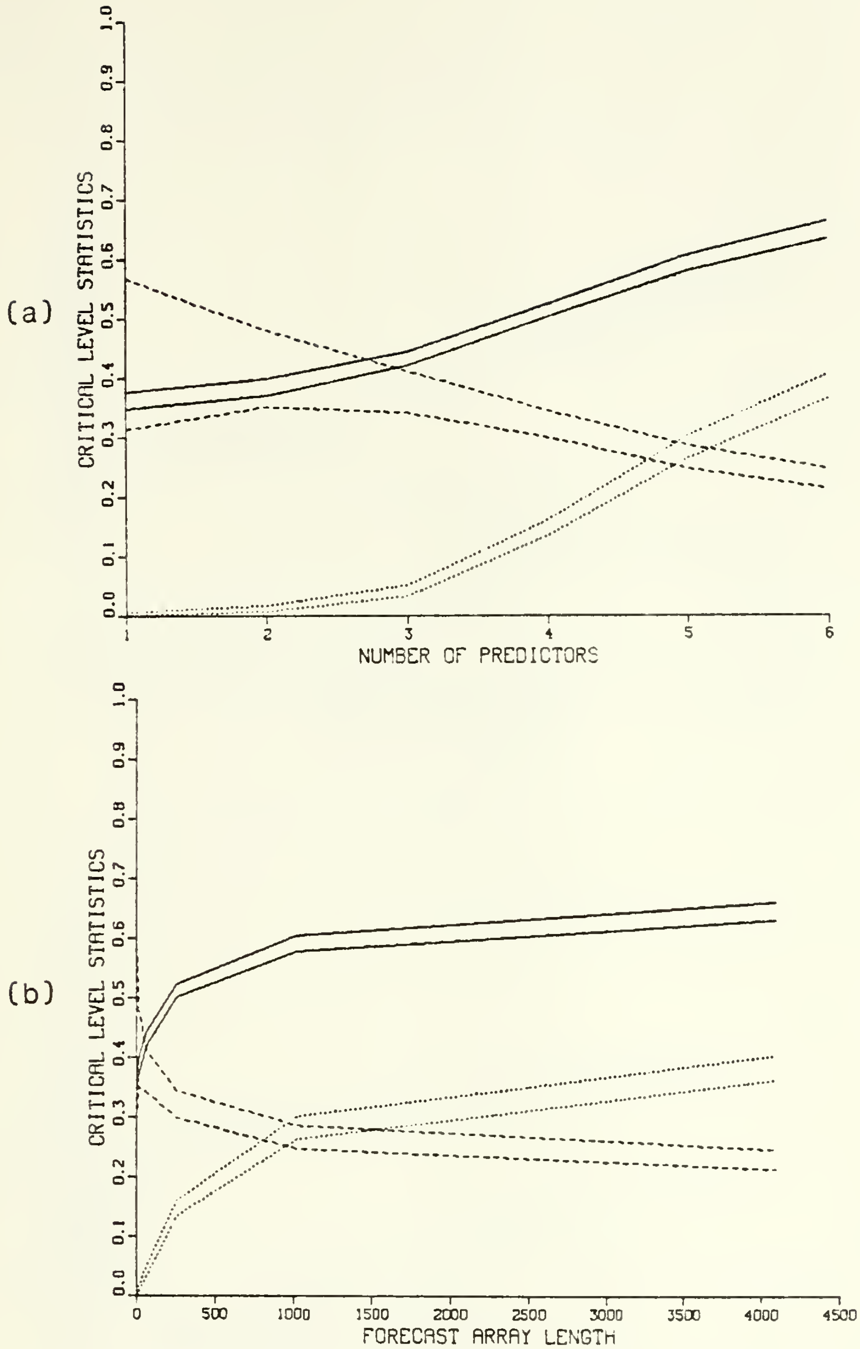
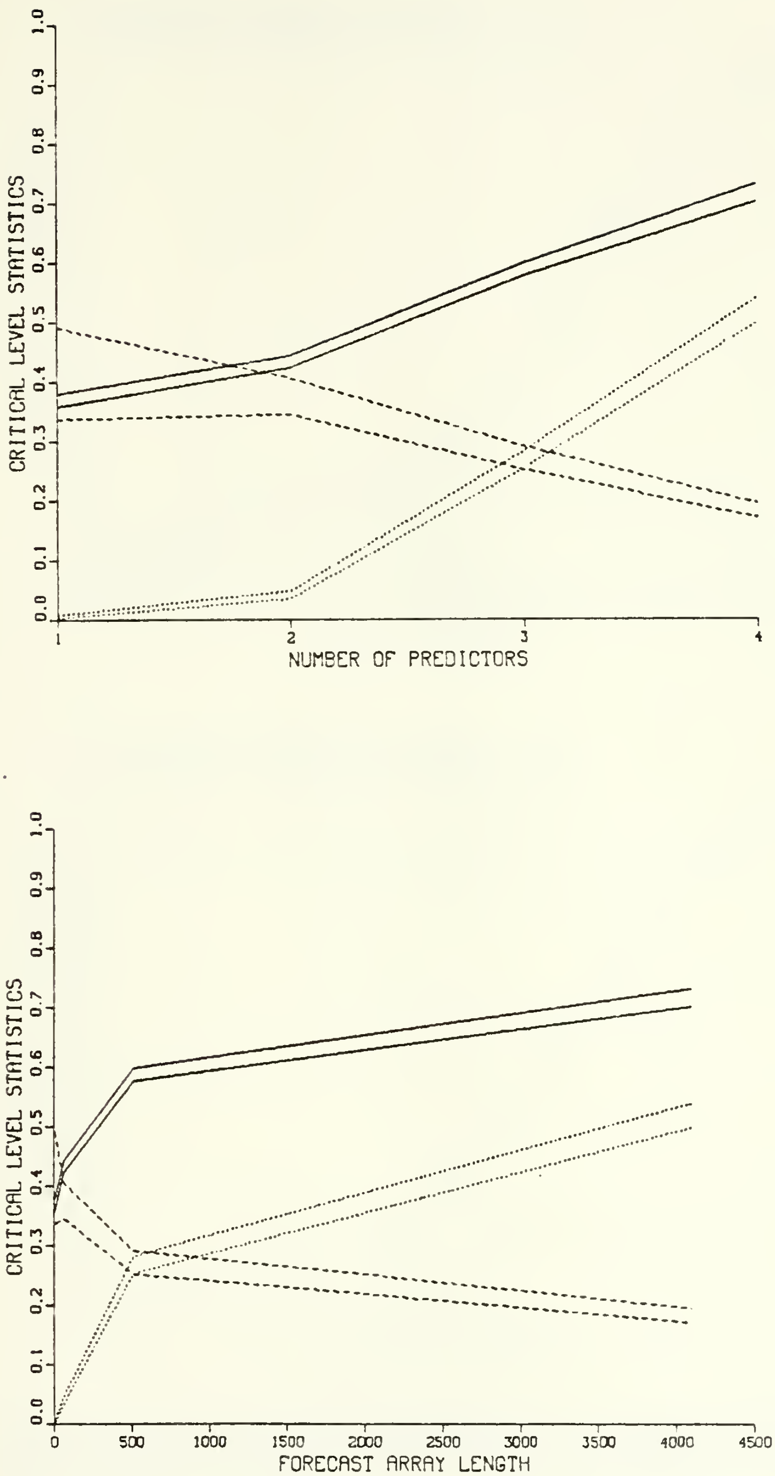


Fig. 8. Behavior of $a_0(96)$ (upper solid), $a_0(05)$ (lower solid), $a_1(96)$ (upper dashed), $a_1(05)$ (lower dashed), PP(96) (upper dotted) and PP(05) (lower dotted) from 100 randomly generated data sets, using predictors from the North Atlantic Ocean area 3W experiment, with each predictor divided into four EPI's, for (a) as each predictor is added and (b) as the forecast array size increases (forecast array size, at any given stage, is equal to the number of EPI's taken to the nth power, where n is equal to the number of predictors included at that stage).

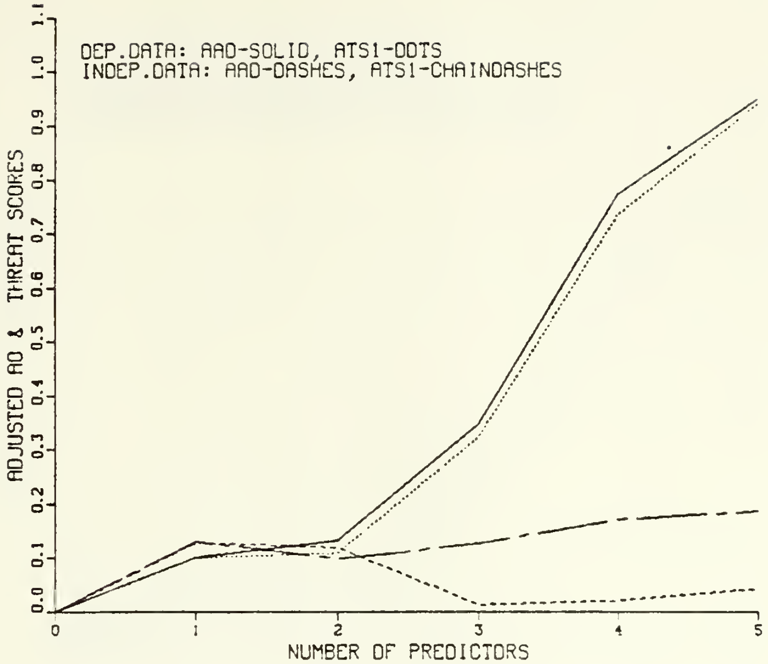
(a)



(b)

Fig. 9. Same as Fig. 8, except each predictor is divided into eight EPI's.

(a)



(b)

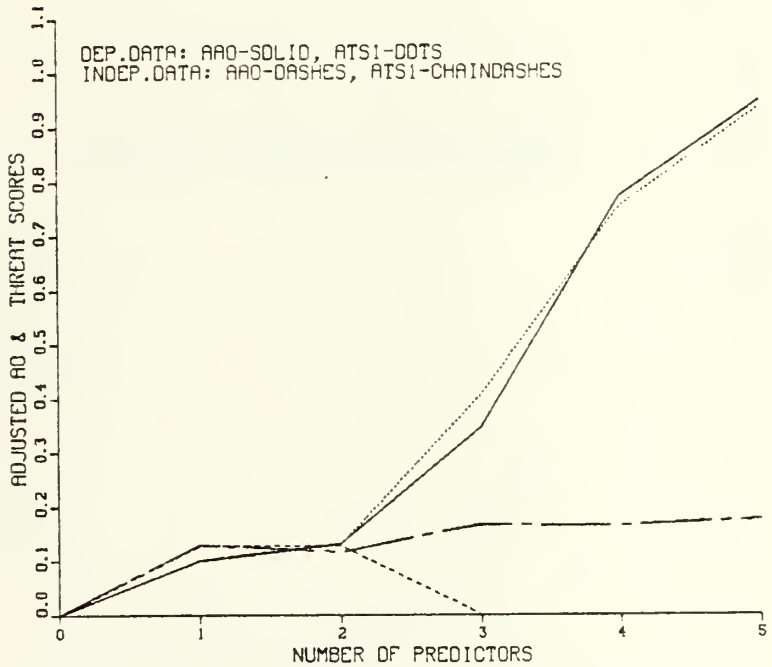
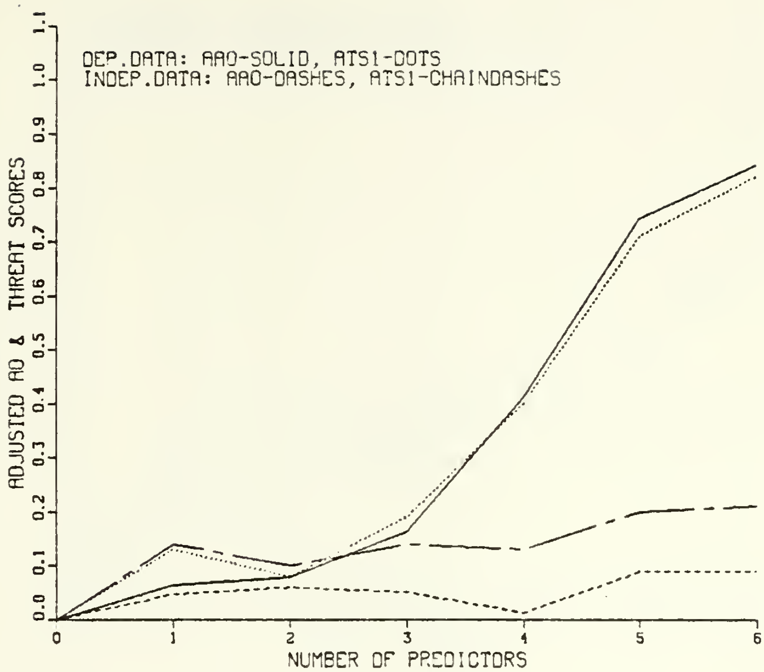


Fig. 10. Contingency table statistics AA0 and ATS1 for both dependent and independent North Atlantic Ocean area 3W, 15 May-15 July 1983, data, without linear-regression equations as predictors, as a function of the number of predictors in the model for strategies (a) MAXPROB1 and (b) MAXPROB2. Predictors are SMF, D850, RH, UBLW and ENTRN, each divided into eight EPI's. Negative values are not plotted.

(a)



(b)

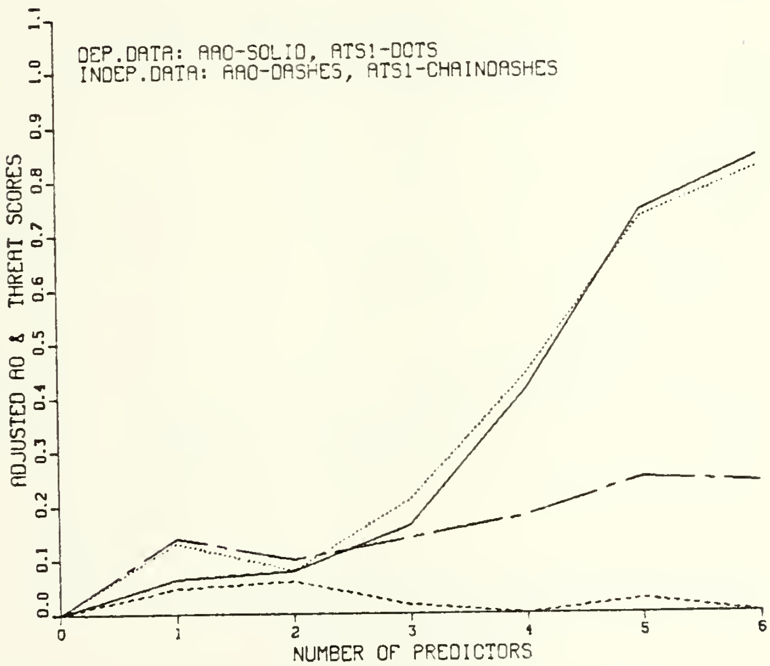


Fig. 11. Same as Fig. 10, except predictors are E925, U700, DVDP, STRTFQ, ENTRN and PS, each divided into five EPI's.

(a) (b)

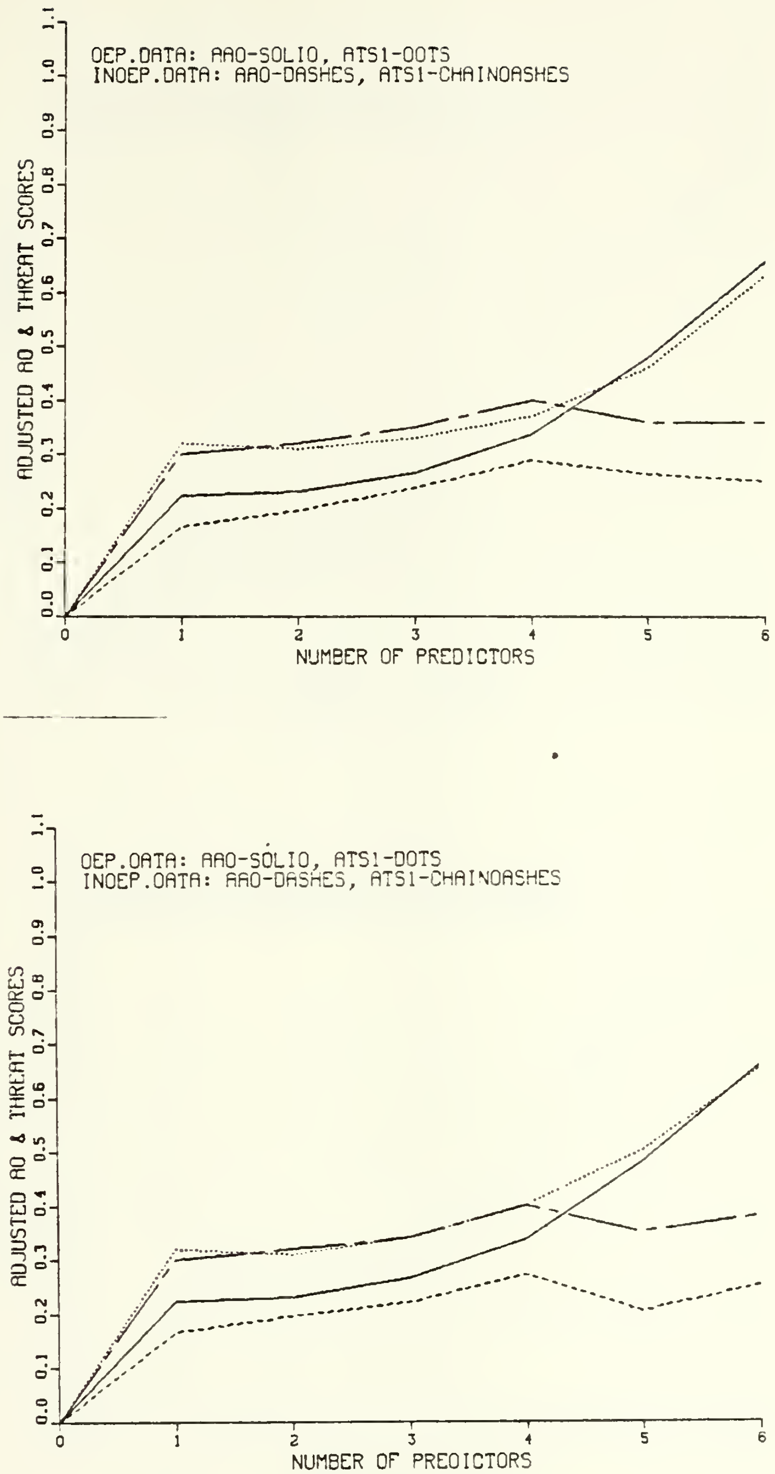
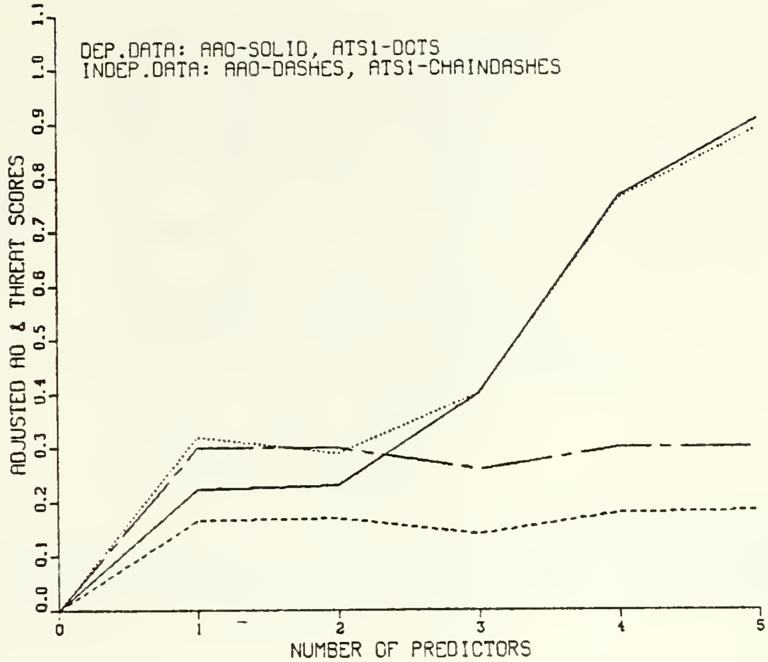


Fig. 12. Contingency table statistics AA0 and ATS1 for both dependent and independent North Atlantic Ocean area 3W, 15 May-15 July 1983, data, with linear regression equations as predictors, as a function of the number of predictors in the model for strategies (a) MAX-PROB1 and (b) MAXPROB2. Predictors are BM1, U850, D500, V850, D1000 and U1000, each divided into four EPI's.

(a)



(b)

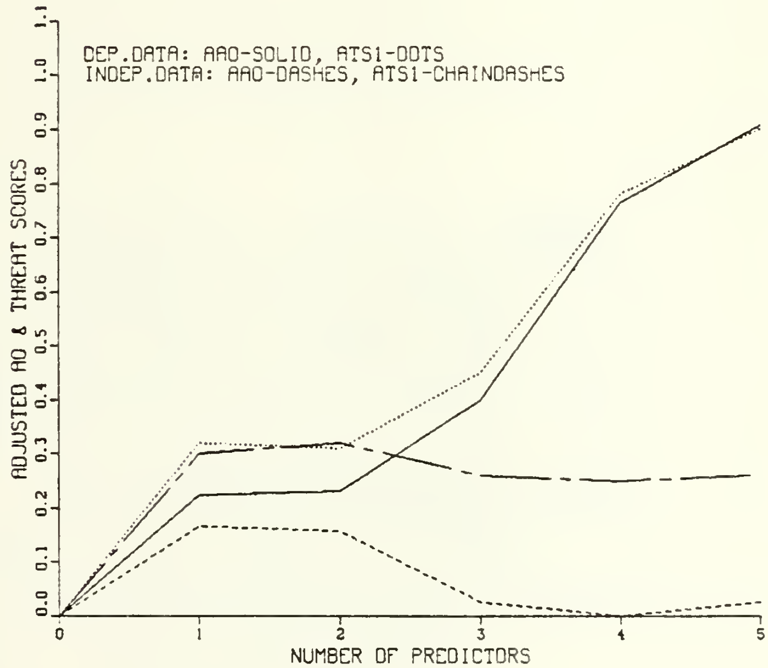


Fig. 13. Same as Fig. 12, except predictors are BM1, U500, ENTRN, DVDP and BM4, each divided into eight EPI's.

VISCAT		Predictor interval i=1	2	3(m)	n(.,j)
3(n)	III	9	25	26	60
2	II	7	7	6	20
j=1	I	17	1	1	19
n(i,.)		33	33	33	99 n(.,.)

Fig. 14. Bivariate plot of EHF as a function of both equally populous intervals (EPI) and visibility categories (VISCAT).

VISCAT	Predictor interval 1	2	3	$p_2(j)$
3	.091	.252	.263	.606
2	.071	.071	.061	.202
1	.172	.010	.010	.192
$p_1(i)$	.333	.333	.333	1.0

Fig. 15. Joint and marginal probabilities of VISCAT's as a function of EPI's for EHF.

VISCAT	Predictor interval 1	Predictor interval 2	Predictor interval 3
3	.273	.758	.788
2	.212	.212	.182
1	.515	.030	.030
	1.0	1.0	1.0

Fig. 16. Conditional probabilities of VISCAT's as a function of EPI's for EHF.

	Conditional probabilities ($i = 1$)	Products
$j=3$	.273	.819
$j=2$	.212	.424
$j=1$	.515	.515
		1.758 $= \sum_{j=1}^{n} j p_{2\,1}(j \mid i)$

Fig. 17. Sample calculation of the average visibility category (VISCAT), natural-regression strategy, for the first EPI (i = 1) of predictor EHF.

$(p_{2\,1}(j|i) - 1/3)^2$

j = 3	.00364	.18034	.20672
j = 2	.01472	.01472	.02290
j = 1	.03300	.09201	.09201

$\sum_{j=1}^{n} (p_{2\,1}(j|i) - 1/3)^2$

.05136	.28707	.32163

pp(i)	.07704	.43061	.48245
$p_1(i)$	.333	.333	.333
$p_1(i)pp(i)$	.02568	.14354	.16082
	i = 1	2	3

$\sum_{i=1}^{m} = .33004 = PP$

Fig. 18. Sample calculation of potential predictability (PP) of visibility by predictor EHI.

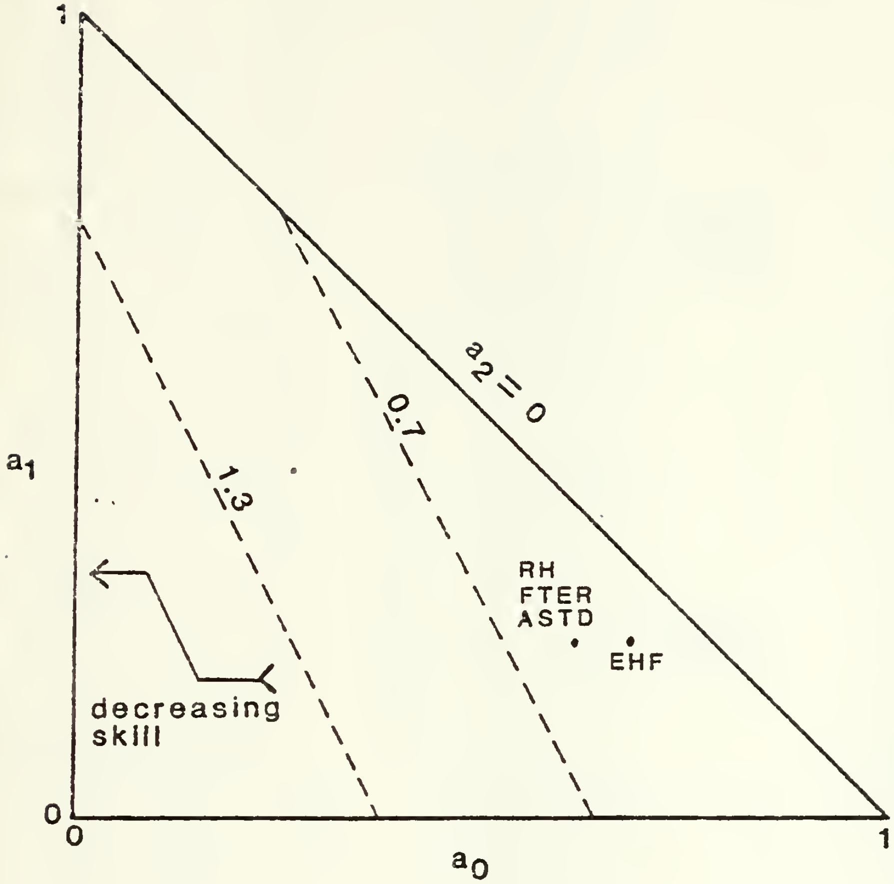


Fig. 19. Skill diagram with lines of constant $a_1 + 2a_2$.

Bivariate plots

	FTER			RH			ASTD		
J = 3	17	17	26	25	22	13	26	16	18
J = 2	8	10	2	5	4	11	3	10	7
J = 1	8	6	5	3	7	9	4	7	8
I =	1	2	3	1	2	3	1	2	3

Conditional probabilities

	FTER			RH			ASTD		
J = 3	.515	.515	.788	.758	.667	.394	.788	.485	.545
J = 2	.240	.303	.061	.152	.121	.333	.091	.303	.212
J = 1	.240	.182	.152	.091	.212	.273	.121	.212	.240
PP =	.211			.225			.209		
a_0 =	.606			.606			.606		
a_1 =	.202			.202			.202		

Fig. 20. Bivariate plots, conditional probabilities, PP's and skill scores, maximum-probability strategy, for predictors FTER, RH and ASTD.

Cell numbering

JJ \ II	1	2	3
3	3	6	9
2	2	5	8
1	1	4	7

VISCAT I

RH \ EHF			
	9	0	0
	7	0	0
	1	1	1

VISCAT II

RH \ EHF			
	3	4	4
	2	1	1
	2	2	1

VISCAT III

RH \ EHF			
	2	5	6
	3	9	10
	4	11	10

Fig. 21a. Tabular presentation of a three-dimensional problem with predictors EHF and RH, each divided into three EPI's, as a function of VISCAT's.

Bivariate plot (II = IGP2(ii-1)+jj)

VISCAT									
III	4	3	2	11	9	5	10	10	6
II	2	2	3	2	1	4	1	1	4
I	1	7	9	1	0	0	1	0	0
II =	1	2	3	4	5	6	7	8	9

Conditional probabilities

.571	.250	.143	.787	.900	.556	.833	.909	.600
.286	.167	.214	.143	.100	.444	.083	.091	.400
.143	.583	.643	.071	.000	.000	.083	.000	.000

Forecast array

3	1	1	3	3	3	3	3	3

Fig. 21b. Reduction of the three-dimensional problem, in Fig. 21a., to two dimensions.

kk = 3	Cell numbering			FTER(3) RH	VISCAT I			VISCAT II			VISCAT III		
3	21	24	27		4	0	0	0	1	0	1	3	4
2	20	23	26		0	0	0	1	0	0	1	3	6
1	19	22	25		0	0	1	0	0	0	0	5	3
					EHF			EHF			EHF		

kk = 2				FTER(2) RH									
3	12	15	18		5	0	0	1	2	2	1	1	1
2	11	14	17		0	0	0	1	1	1	1	3	2
1	10	13	16		0	1	0	1	0	1	1	1	6
					EHF			EHF			EHF		

kk = 1				FTER(1) RH									
3	3	6	9		0	0	0	2	1	2	0	1	1
2	2	5	8		7	0	0	0	0	0	1	3	2
jj = 1	1	4	7		1	0	0	1	2	0	3	5	1
	ii = 1	2	3		EHF			EHF			EHF		

Fig. 22a. Tabular presentation of a four-dimensional problem with predictors EHF, RH and FTER, each divided into three EPI's, as a function of VISCAT's.

Bivariate plot (II = IGP2(ii-1+IGP1(kk-1))+jj)

VISCAT	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
III	3	1	0	5	3	1	1	2	1	1	1	1	1	3	1	6	2	1	0	1	1	5	3	3	3	6	4
II	1	0	2	2	0	1	0	0	2	1	1	1	0	1	2	1	1	2	0	1	0	0	0	1	0	0	0
I	1	7	0	0	0	0	0	0	0	0	0	5	1	0	0	0	0	0	0	0	4	0	0	0	1	0	0

Forecast array

3	1	2	3	3	2	3	3	2	2	2	1	1	3	2	3	3	2	0	2	1	3	3	3	3	3	3
																		3	Default value from column 1 Fig. 21b							

Fig. 22b. Reduction of the four-dimensional problem, in Fig. 22a., to two dimensions.

Bivariate plot

RH			
	14	9	10
	12	10	11
	7	14	12
	i = 1	2	3

EHF

Joint probabilities

j			
3	.141	.091	.101
2	.121	.101	.111
j=1	.071	.141	.121
	1	2	3

EHF

Conditional probabilities

.424	.273	.303
.364	.303	.333
.212	.424	.364
1	2	3

EHF

q(i,j)

0	.576	.727
.273	.515	.424
.576	.636	0

r(i,j)

.727	.697	0
.424	.788	.273
0	.788	.576

|q(i,j)−r(i,j)|

.727	.121	.727
.151	.273	.151
.576	.152	.576

$m = 3$ $\qquad$ $m/2(m-1) = .75$

$$FD(2|1) = FD(RH|EHF) = .75(.141(.727) + .121(.151) + .071(.576) + .091(.121) + .101(.273) + .141(.152) + .101(.727) + .111(.151) + .121(.576)) = .286$$

Fig. 23. Sample calculation of functional dependence (FD) of RH on EHF.

Uniform incremental probabilities

j	
3	1.00
2	.66
1	.33

Incremental probabilities

i	1	2	3	4	5	6	7	8	9
$p_1(i)$	.071	.121	.141	.141	.101	.091	.121	.111	.101
	.071	.192	.333	.474	.575	.666	.787	.898	1.0

Fig. 24. Example of incremental marginal probabilities for a bivariate predictor (EHF and RH), derived from Fig. 21b., and uniform probabilities for VISCAT's, used to generate random data sets by monte-carlo means.

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